Estimating The Continuous Risk Of Accidents Occurring In The South African Mining Industry

by

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Declaration

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Abstract

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Statistics from mining accidents expose that the potential for injury or death to employees from occupational accidents is relatively high. This study attempts to contribute to the on-going efforts to improve occupational safety in the mining industry by creating a model capable of predicting the continuous risk of occupational accidents occurring. Model inputs include the time of day, time into shift, temperatures, humidity, rainfall and production rate. The approach includes using an Artificial Neural Network (ANN) to identify patterns between the input attributes and to predict the continuous risk of accidents occurring. As a predecessor to the development of the model, a comprehensive literature study was conducted. The objectives of the study were to understand occupational safety, explore various forecasting techniques and identify contributing factors that influence the occurrence of accidents and in so doing recognise any gaps in the current knowledge. Another objective was to quantify the contributing factors identified, as well as detect the sensitivity amongst these factors and in so doing deliver a groundwork for the present model.

After the literature was studied, the model design and construction was performed as well as the model training and validation. The training and validation took the form of a case study with data from a platinum mine near Rustenburg in South Africa. The data was split into three sections, namely, underground, engineering and other. Then the model was trained and validated separately for the three sections on a yearly basis. This resulted in meaningful correlation between the predicted continuous risk and actual accidents as well as the majority of the actual accidents only occurring while the continuous risk was estimated to be above 80%. However, the underground section has so many accidents, that the risk is permanently very high. Yet, the engineering and other sections produced results useful for managerial decisions.

Uittreksel

Beraming van die Deurlopende Risiko van Ongelukke In Die Suid-Afrikaanse Mynbedryf

("Estimating The Continuous Risk Of Accidents Occurring In The South African Mining Industry")

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Mynbou ongeluk statistieke dui aan dat die potensiaal vir besering of dood as gevolg van beroepsongelukke relatief hoog is. Die studie poog om by te dra tot die voortdurende verbetering van beroepsveiligheid in die mynbedryf deur middel van 'n model wat die risiko van beroepsongelukke voorspel. Die model vereis die tyd, tyd verstreke in die skof, temperatuur, humiditeit, reënval en produksie tydens die ongeluk as inset. Die benadering tot hierdie model maak gebruik van 'n Kunsmatige Neurale Netwerk (KNN) om patrone tussen die insette te erken en om die risiko van 'n voorval te beraam. As 'n voorloper tot die model ontwikkeling, is 'n omvattende literatuurstudie onderneem. Die doelwitte van die literatuur studie was om beroepsveiligheid beter te verstaan, verskeie voorspellings tegnieke te ondersoek en kennis van bydraende faktore wat lei tot voorvalle te ondersoek. Nog 'n doelwit sluit die kwantifisering in van geidentifiseerde bydraende faktore, asook die opsporing van die sensitiwiteit tussen hierdie faktore en hierdeur 'n fondasie vir die voorgestelde model te skep.

Na afloop van die literatuurstudie is die model ontwikkel, opgelei en gevalideer. Die opleiding en validasie is deur middel van 'n gevallestudie in 'n platinummyn naby Rustenburg in Suid Afrika gedoen. Die data is verdeel in drie afdelings, d.i. ondergronds, ingenieurswese en ander. Die model is vir elke afdeling apart opgelei en gevalideer op 'n jaarlikse basis. Hierdie het gelei tot 'n betekenisvolle korrelasie tussen die voorspelde risiko en die werklike ongelukke met die meerderheid van die werklike ongevalle wat voorgekom het terwyl die risiko 80% oorskry het. In die ondergrondse afdeling is so baie voor-

valle waarneem dat die risiko permanent hoog is. Die ander afdelings het wel resultate verskaf wat sinvol gebruik kan word in bestuursbesluite.

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The Author
September 2014

Dedications

This thesis is dedicated to my
family and friends, for their continued
understanding, patience and love.

Contents

List of Figures

List of Tables

Acronyms

AEA	Action Error Analysis
ALARP	As Low As Reasonably Practicable
ANN	Artificial Neural Networks
CEO	Chief Executive Officer
CTD	Cumulative Trauma Disorders
D/R/C	Detectability/Revocability/Consequence
DMR	Department of Mineral Resources
ET	Event Trees
FI	Fatal Injury
FIFR	Fatal Injury Frequency Rate
FMEA	Failure Modes & Effects Analysis
FMECA	Failure Modes, Effects & Criticality Analysis
FOG	Fall Of Ground
FRAM	Functional Resonance Accident Model
FT	Fault Trees
FTA	Fault Tree Analysis
GOMS	Goals, Operators, Methods and Selection

HAZOP	Hazard & Operability Study
HMM	Hidden Markov Model
HPI	High Potential Incident
ICU	Intensive Care Unit
ILCI	International Loss Control Institute causation model
INRS	National Institute for Research & Safety model
LTI	Lost Time Injury
LTIFR	Lost Time Injury Frequency Rate
LTISR	Lost Time Injury Severity Rate
MHSA	Mine Health and Safety Act
MLP	Multilayer Perceptron
MORT	Management Oversight & Risk Tree
MSE	Mean Square Error
MTC	Medical Treatment Case
NPV	Negative Predictive Value
NSC	National Safety Council
OARU	Occupational Accident Research Unit deviation model
OHSA	Occupational Health and Safety Act
PCA	Principal Component Analysis
PERT/CPM	Program Evaluation & Review Technique - Critical Path Method
PHA	Preliminary Hazard Analysis
PPE	Personal Protective Equipment

PPV	Positive Predictive Value
SEM	Structural Equation Model
SHA	Systems Hazard Analysis
SHERPA	Systematic Human Error Reduction and Prediction Approach
SI	Serious Injury
SLIM-MAUD	Subjective Likelihood Index Methodology
SMORT	Safety Management and Organisation Review Technique
STAMP	Systems-Theoretic Accident Model & Processes
STARS	Software Tools for Analysis of Reliability and Safety
STEP	Sequentially Timed Events Plotting
SVM	Support Vector Machine
THERP	Technique for Human Error Rate Prediction
TNR	True Negative Rate
TPR	True Positive Rate
UBI	Unsafe Behaviour Index
UK	United Kingdom
USA	United States of America
WBGT	Wet Bulb Globe Temperature
WSA	Work Safety Analysis

Nomenclature

Network Architecture

u	Input attribute value
w	Weight from input to node
net	Output from node summation
Φ	Output from hidden layer activation function
$\hat{y}$	Output from output layer node

Training Error

E	Error function
d	Training example
D	Set of training examples
k	Output
O	Set of output nodes
t	Target value
o	Output value

Back-Propagation

η	Learning rate
δ	Error responsibility
x	Input to node
α	Momentum

Sensitivity Analysis

$\bar{u}$	Mean input
$\bar{\hat{y}}$	Mean output

Chapter 1

Introduction

1.1 Introduction

This chapter serves the purpose of an introduction to the research undertaken, covering the fundamentals of this entire study. In addition, this chapter deliberates the background of the study along with where this research fits into the existing body of knowledge, as well as the significance of the research performed. This is followed with the problem statement which is explored throughout the thesis. Next, the delimitations of the research are discussed along with the objectives of the research in order to give boundaries in which the study will be conducted. After which the research design and methodology is discussed to designate the method used going about evaluating the null hypothesis. Lastly, this chapter is concluded with the outline to be followed during the course of the rest of the thesis.

1.2 Background of Study

"Safety is a cheap and effective insurance policy" – Author unknown

According to the Occupational Health and Safety Act (OHSA) of South Africa as stated by the South African Department of Labour (2004), "every employer shall provide and maintain, as far as is reasonably practicable, a working environment that is safe and without risk to the health of his employees." Since the OHSA is a legal requirement for all and sundry in South Africa, this brands the theme of safety more dominant in all forms of industry. Thus, in any organisation no matter what their core method of income generation is, a primary concern of theirs is the safety of their employees. Groves *et al.* (2007) discover that this is even more evident in the industries with higher risks towards employee safety such as mining, as there are many more risks at play and an injury can be very costly towards the organisation. However, Lapere (2013) discusses with regards to mining, that the OHSA is not applicable to any matter in respect of which any provision of the Mine Health and

Safety Act (MHSA) is applicable. Nonetheless, the MHSA still insists that employers do everything possible to provide conditions for safe operation and a healthy working environment as well as ensure that employees can perform their work without endangering the health and safety of themselves or of any other person as stated by the South African Department of Mineral Resources (1996). A mine can be defined as an excavation in the earth from which ore, minerals and industrial commodities can be extracted, and this includes large and small scale operations.

The South African mining industry realised 123 fatalities in 2011 and 112 fatalities in 2012 across all the mines in the country. Furthermore, South Africa realised 3299 injuries in 2011 and 3377 injuries in 2012 across all the mines in the country as published by South African Department of Mineral Resources (2013*g*) in their *Annual Report 2012/2013*. These statistics can be divided up and sorted according to individual commodities as can be seen in Table 1.1. A fatality rate and injury rate is included in the table, it indicates the rate of accidents per million man hours and its calculation can be seen later in Equation 2.2.1 and 2.2.2.

Table 1.1: South African mining fatalities and injuries and their rates per commodity 2011/2012 (adapted from South African Department of Mineral Resources (2013*g*) Annual Report 2012/2013)

Commodity	**Fatalities**		**Fatality Rate**		**Injuries**		**Injury Rate**	
	2011	**2012**	**2011**	**2012**	**2011**	**2012**	**2011**	**2012**
Gold	51	51	0.17	0.18	1498	1478	5.07	5.13
Platinum	37	28	0.09	0.07	1283	1360	3.2	3.43
Coal	12	11	0.07	0.06	241	267	1.44	1.51
Diamonds	3	2	0.11	0.07	42	48	1.58	1.78
Copper	1	1	0.14	0.15	19	13	2.66	1.9
Chrome	5	4	0.14	0.1	71	77	1.99	1.96
Iron Ore	0	2	0	0.04	20	20	0.39	0.39
Manganese	2	0	0.13	0	13	15	0.82	0.8
Other	12	13	0.12	0.12	112	99	1.12	0.9
All Mines	123	112	0.11	0.1	3299	3377	3	3.03

The South African Department of Mineral Resources (2013*c*) has established targets to reduce occupational fatalities as well as occupational injuries in the mining sector by 20% per year over the period of 2013 to 2016 as recorded in their *Annual Performance Plan 2013/2014*. From Table 1.1, it can be easily identified that the gold and platinum mines are the largest contributors to mining fatalities and injuries in South Africa, however, this is with respect to the number of accidents occurring. When looking at the fatality and injury rates, which express these accidents per million man hours, which makes use of the number of employees, this then identifies the most dangerous mining operations by commodity are again the gold and platinum mines. However, the copper, chrome and diamond mines hit the radar as also being dangerous. Thus, in order to make the largest impact, focus should be placed on reducing the fatalities and injuries in the gold and platinum mines. Furthermore, there are far more injuries as opposed to fatalities and thus again the largest area for improvement would be in reducing the injuries within the gold and platinum mining areas.

Hofmann and Tetrick (2003) state that an organisation's well-being depends largely on its employee's well-being. Furthermore, Clarke and Cooper (2004) state that 60% to 80% of all workplace accidents are due to work place stress and as such human behaviour is the biggest variable in industry, consequently it is where the majority of risks originate from. Organisations are continuously attempting to find ways to minimise the risks their employees are exposed to, however, if these risks cannot be minimised, then exposure to the risks is minimised as identified by HSE (1997). Yet, this is not such a simple undertaking and occasionally employees will be exposed to known risks. A classification of some such known risks can be seen in Table 1.2, which represents the fatalities during 2011 and 2012 sorted by classification of risk. Controls are typically set in place to protect the employee while being exposed to these known risks, such as Personal Protective Equipment (PPE) and regulations of how work is to be executed in the safest possible manner.

Although organisations do what they can to mitigate known risks, it is impossible to eradicate them all, at which point the organisation is required to decide if it is an acceptable risk or if different processes need to be put in place in order to bypass the risk, as it is known that being exposed to risks has the inherent potential for injuries to occur. For example, automation in underground mines to elude the danger of Fall Of Ground (FOG) injuries. HSE (1997) state that all accidents and incidents are preventable, yet they somehow still occur in industry. For the purpose of this study, an accident refers to any undesired circumstances which give rise to ill health or injury, whereas an incident refers to all near misses and undesired circumstances which have the potential to cause harm.

Above, fatalities and injuries are discussed. In the mining sector, these two classifications are used along with three more classifications. Thus, there are five common classifications, which are Fatal Injury (FI), Serious Injury (SI), Lost Time Injury (LTI), Medical Treatment Case (MTC) and High Potential Incident (HPI). A FI corresponds to an accident that occurs where an employee loses their life, a SI refers to an accident that causes a person to be admitted to a hospital for treatment for the injury, a LTI refers to an accident that occurs where an employee is injured and has to spend more than one complete

Table 1.2: South African mining fatalities per risk classification 2011/2012 (adapted from South African Department of Mineral Resources (2013*g*) Annual Report 2012/2013)

Classification	**2011**	**2012**
Fall Of Ground (FOG)	40	26
Machinery	5	8
Transportation and mining	38	29
General	25	35
Conveyance accidents	3	1
Electricity	3	5
Fires	0	0
Explosives	4	4
Subsidence/caving	0	1
Heat sickness	2	2
Miscellaneous	3	1
Total	123	112

day or shift away from work as a result of the accident and a MTC refers to any injury that is not a LTI, but does require treatment. Furthermore, a near miss is recorded as a High Potential Incident (HPI), this is when an event has the potential to cause a significant adverse effect on the safety and health of a person.

In the mining industry, dealing with multiple known risks that employees are exposed to daily, it is an everyday problem knowing when an accident will occur. Furthermore, Wu *et al.* (2008) state there is a lack of knowledge in safety modelling, which is very useful and vital in industries which deal with risks daily that cannot be further mitigated. Knowing this, it would be very useful to be able to estimate the continuous risk of accidents occurring such that proactive measures can be put in place in order to reduce the probability of an injury occurring. Thus, the success of this research in estimating the continuous risk of accidents occurring before any accident occurs, will prove to be tremendously valuable to the mining industry, as well as to the currently tiny body of knowledge around predictive safety modelling. Moreover, the created model will have the potential to be adapted to other industries dealing with known risks.

Grimaldi and Simonds (1989) found that the cost of work related accidents for 1985 was estimated by the National Safety Council (NSC) to be US $ 37.3 billion. This was a conservative value and did not include loss of future earnings or productivity due to workers being killed or permanently impaired. Furthermore this did not include the full economic impact on the families of seriously injured workers. Moreover, National Safety Council (2014) identified that in 2012 the average economic cost of a death was US \$ $1,400,000$ per case and of a disabling injury was US \$ $53,000$ per case. These figures were an average cost of wage and productivity losses, medical expenses and administrative expenses, and did not include any estimate of property damage or non-disabling injury costs. With injuries being so costly, it is imperative to put forward new ideas in attempt to make the workplace a safer place.

1.3 Problem Statement

In all forms of industry, employee safety is an essential aspect to the organisation's operations regardless of the risks that the employees are exposed to. It follows that any accidents which endanger human safety are intolerable. Furthermore, people are becoming numb to safety warnings, which exposes the problem of *how does a person know when the risk of an accident occurring will be of a high level for concern* in order to be able to intervene and attempt to prevent it. Additionally, what set of circumstances warrant renewed or additional effort to prevent or reduce the risk. This is a problem due to the fact that the occurrence of an accident could be a violation of South African laws as well as being costly towards an organisation in respect of medical claims, as well as lost productivity time and lowered employee efficiency as identified by Grimaldi and Simonds (1989). Following on from this, there is a large knowledge gap in this field of predictive safety modelling identified and as such this is where the scope of this research is aimed at fitting in.

The purpose of this research is to develop a model in the field of predictive modelling in a safety environment, dealing with the exposure of employees to known risks. Furthermore, this will add to the currently lacking body of knowledge around predictive safety modelling.

From the above discussed problem, the following null hypothesis is derived,

H_0:	*'A multivariate mathematical model cannot be used to link circumstantial variables to estimate the continuous risk of accidents occurring pertinent to the South African mining industry.'*

1.4 Delimitations

In research, it is imperative to set boundaries in order to not get distracted as well as to keep focus throughout the study. The focus for this study is on creating a model for estimating the continuous risk of accidents occurring, which needs to stay within the following boundaries:

- This study will include Fatal Injuries (FI's), Severe Injuries (SI's), Lost Time Injuries (LTI's), and Medical Treatment Cases (MTC's) for the predictive model.
- This study will not include any High Potential Incidents (HPI's) in the predictive model, because they are not actual accidents, as well as there being so many, thus they will over complicate the model.
- This study is bound to the South African mining industry.
- The case study will only use data from one platinum mine in South Africa, assuming the data is similar across all platinum mines.

This concludes the delimitations for this research.

1.5 Research Objectives

The aim of this research is to mathematically estimate the continuous risk of accidents occurring within confidence bands. In order to achieve this aim, the following research objectives are set to guide the research.

1. To understand occupational safety.
2. To explore the functions of various existing forecasting techniques.
3. To identify contributing factors that influence accidents.
4. To quantify these contributing factors that influence accidents.
5. To detect the sensitivity of these contributing factors that influence accidents.
6. To establish a model, combining circumstantial variables, for estimating the continuous risk of accidents occurring.

This concludes the research objectives for this research.

1.6 Research Design and Methodology

Research can be divided into two main kinds of research, namely, quantitative and qualitative. According to Leedy and Ormrod (2013), quantitative research involves looking at quantities or amounts of one or more variables such that the variables can be measured in a numerical way. In contrast to this, Leedy and Ormrod (2013) state that qualitative research looks at characteristics or qualities that cannot be reduced to numerical values. Human behaviour and workers moral is an example of qualitative data, whereas production rate and number of accidents is an example of quantitative data. Despite the relative strengths and weaknesses of these two approaches, often a more complete picture can be created by combining elements of both approaches, Leedy and Ormrod (2013) refer to this as mixed-methods.

With regards to the research design and methodology for this thesis, initially key areas for investigation will be identified with respect to the research problem. Thereafter, a literature study of these key areas will be performed to understand what has been done in the past and learn what techniques will work best in this research.

Next, the type and availability of data will be investigated. This will steer the direction of the research as it is essential for the model. This data will be contextualised and a proposed solution will be designed. A mixed-methods approach will be taken, as the data and inputs to the model is probable to be of a quantitative and qualitative nature. Furthermore the model will be verified through the use of additional independent data, and lastly the model will be validated through the method of a case study.

1.7 Thesis Outline

This section provides a summary and breakdown of the layout and content in the rest of the document. The document has a logical layout portraying the research in the order it was completed. Furthermore, the research objectives are progressively answered through the rest of the study in this logical layout.

Chapter 1: Introduction
Chapter 1 is the introductory section, which explains the background and research problem as well as the delimitations and research objectives which will direct the research towards evaluating the null hypothesis.

Chapter 2: Literature Study
Chapter 2 introduces the fundamentals of safety and risk, along with factors that influence accidents. This is followed by an overview of some modelling techniques along with a comparison of them in order to identify the best technique.

Chapter 3: Design And Construction Of The Model
Chapter 3 presents an overview of the model for the proposed solution, followed by a detailed look into the mathematics Artificial Neural Networks (ANN). This is followed with an analysis of the data used in the model, as well as calculating normalised continuous approximation of the influential factors and explaining the setup of the data for the model.

Chapter 4: Training And Validation Of The Model
Chapter 4 presents the method of training and validating the model, followed by the results from the training and validation, after which a sensitivity analysis of the inputs to the model is performed and lastly the intended use of the

model is discussed.

Chapter 5: Conclusion

Chapter 5 brings closure to the study, through a brief summary of the study, a discussion of some limitations and recommendations for future research, which is followed by a final conclusion of the research.

Chapter 2

Literature Study

2.1 Introduction

"A man who reviews the old so as to find out the new is qualified to teach others" – Confucius

Badenhorst (2008) states that all research is grounded on prior research and thus a literature review is essential to identify and deliberate where this research emerges from previous research. In addition, Hofstee (2006) identifies that a good literature review must be comprehensive, critical and contextualised such that the reader is provided with a theory base, a review of suitable published works and an analysis of that work. With this in mind, this literature study can be broken down into the following sections, (1) Safety[1], (2) Risks, (3) Influencing Factors and lastly (4) Forecasting Techniques.

In the first section on safety, aspects of organisational safety cultures will be explored, comprising of safety leadership, safety climates, safety performance, their inter-relationship as well as current safety models. Next, the section on risks will explore what risk is, how it is approached, how it should be managed, as well as the known risks a person is exposed to while working on a South African mine. Then the section on influencing factors focuses on the various factors which are known to influence the occurrence of an accident. This includes human factors, machine factors, environmental factors and management factors. Lastly, multiple modelling techniques will be researched to identify the most appropriate techniques required for the predictive model.

[1]Safety Management written by Grimaldi and Simonds (1989) was first written in 1956 and it redefined the work of safety specialists. It was widely adopted globally from students to experienced practitioners. Furthermore, it introduced the phrase safety management, which later became the universal description for the work of safety practitioners generally. Moreover, every revision was influenced by anonymous reviewers and the public's criticisms and advice, refining the book and increasing its usefulness and the 5th (latest) revision was published in 1989. With this in mind, Grimaldi and Simonds (1989) work is used as a foundation for this review on safety.

2.2 Safety

O'Toole (2002) recognises that with limited resources to help diminish occupational injuries, companies struggle with how to optimally focus their resources to attain the maximum reduction in injuries for the lowest cost. Furthermore, Grimaldi and Simonds (1989) identify that typically, top management prefer to know that safety measures put in practice will function to increase the all-around efficiency of their departments rather than constitute an increase in cost and a hindrance on production.

It is generally known that occupational safety is of importance in any organisation and thus accident prevention should be important on the list of organisational activities performed. Hovden *et al.* (2010) describe an accident, as a hazard becoming visible in a sudden probabilistic event (or chains of events) with adverse consequences. In terms of occupational accidents, these adverse consequences can be viewed as employee injuries. This definition is confirmed by Hoyos *et al.* (1988), who define an accident in more simple terms as, a set of undesirable conditions that can lead to a collision between a person and an object. Thus, in accident prevention, the aim is to remove the undesirable conditions or break the chain of events leading up to the accident.

In addition, Grimaldi and Simonds (1989) define an accident as *"an event or condition occurring by chance or arising from an unknown or remote cause."* However, Grimaldi and Simonds (1989) identify that nine out of ten occupational injuries can be predicted. In this study, an accident refers to any undesirable circumstances which give rise to ill health or injury. As well as, an incident referring to all undesired circumstances and near misses which have the potential to cause harm.

Hoyos *et al.* (1988) declare that hazardous situations can only arise if a person is exposed to a hazard. According to Grimaldi and Simonds (1989), in practice, safety appears to have a low priority among the government for human well-being until the public is sufficiently aroused by being exposed to accident reports and information. Despite the OHSA legally enforcing that all employers must ensure the safety of their employees, Grimaldi and Simonds (1989) identify that knowing these legal requirements will not optimise safety, though it will create a climate which can be used for the development of safety strategies to optimise safety.

As stated by Grimaldi and Simonds (1989), a simple matter of applying particular procedures is often how safety is regarded, yet, an effective safety management system entails more than just this. In practice, often safety requirements are seen to conflict with other requirements such as productivity, convenience or other factors. However, when there is sufficient motivation for safe action, then safety requirements may have preference over other needs, for example, when a task needing to be performed is known to be very dangerous. Additionally, Hoyos *et al.* (1988) articulate the fact that safety experts understand that accident prevention depends more on human factors than on an engineering source. These human factors can be complex and are more than just employee negligence, which is defined by Grimaldi and Simonds (1989) as the creation of unreasonable risk without intending to cause harm.

Despite the legal and moral implications of accidents, Hoyos *et al.* (1988) establish that accidents have economic dimensions as well. Some examples of costs involved in an occupational injury include

- ✧ Hospital costs, compensation costs, pensions, reparation costs, etc.
- ✧ Court costs for claims proceedings
- ✧ Costs for rescue measures and gear
- ✧ "Use" of first aid gear
- ✧ Loss of a person's ability to function and resulting loss of income
- ✧ Stoppage or reduction of operations as long as an inquiry into the circumstances surrounding the accident is being conducted and the consequences of the accident have not been fully accounted for
- ✧ Costs for the training of replacements
- ✧ Time lost for persons not directly involved with the accident
- ✧ Loss of reputation

Grimaldi and Simonds (1989) identify that significant savings both in human suffering and in profits are possible through effective safety efforts. Thus a well implemented safety system should reduce the risk of an incident as well as save money.

Safety should be viewed holistically, as it is a developing property of systems that comes from the interaction of system components as identified by Leveson (2004). He suggests that a plant's safety cannot be determined by inspecting a single valve in the plant. Facts about the situation in which that valve is used is also crucial. Thus, it is impossible to take a single system component in isolation and evaluate its safety. A component that is completely safe in one system may not be when used in another.

As stated by Hermanus (2007), the mining sectors accident and ill-health records compare below par to that of other economic sectors such as manufacturing, construction and rail. This leads to the reputation that the mining sector is the most hazardous industrial sector. Therefore, knowing the importance of mining to employment and the economy, there is substantial worth in addressing health and safety methodically. Moreover, in the broader framework of sustainable development, among the first expectations are healthy and safe working conditions, which ensure workers are not denied of their livelihoods or of their quality of life.

In a comparison completed by Hermanus (2007), it was established that South African miners are 4 to 5 times more likely to lose their lives in mine accidents than in Australia. However, it was not established if this was due to different mining technology used or different management styles etc. Paul and Maiti (2005) agree with Hermanus (2007), stating that mining is considered one of toughest and most hazardous occupations. Paul and Maiti (2005) continue that underground mine-workers have to work in severe working conditions in narrow openings with substantial heat and humidity, heavy noise and vibration, poor illumination, airborne dust and noxious gases. These physical hazards bring about a serious problem in handling the safety and health risks of mine workers. As a result, accidents/injuries are prevalent across all commodities in underground mining.

2.2.1 Safety leadership

According to Grimaldi and Simonds (1989) safety is not of the uppermost importance in an individual's mind and thus external governance is required to provide some regularity in the behaviour necessary for safety to be achieved. Grimaldi and Simonds (1989) go on to define safety management as, "applying steps to assist executive decisions about safety and to make use of the managerial hierarchy to establish and maintain a visible active safety posture within the organisation." Very similarly, Wu *et al.* (2008) identify safety leadership as "the process of interaction between leaders and followers, through which leaders could exert their influence on followers to achieve organisational safety goals under the circumstances of organisational and individual factors."

As stated by Hoyos *et al.* (1988), management's commitment to safety, such as assigning further capital, giving accident prevention a greater precedence, etc. is influential with respect to the success of safety efforts. Hofmann and Tetrick (2003) add that leadership variables have a direct effect on safety records, however, when leadership has done all it can do, accidents still occur. Moreover, it is impossible to realise absolute safety, thus equilibrium must be found amongst risk and utility. Furthermore, Grimaldi and Simonds (1989) identify hazard elimination, not accident elimination, as a primary apprehension of safety management. This is due to hazard elimination removing the danger and as such, an accident cannot occur. Grimaldi and Simonds (1989) go on to say that as injuries are brought under control, it becomes more difficult to continue major reductions, thereafter a program to maintain the accident reductions is required.

Wong (2010) reveals the fact that unfortunately management is often solely engrossed on the management of risks associated with financial gain and they tend to overlook the need to manage the risk of losing their material and human assets as well as the devastating impact that could have on their business. However, O'Toole (2002) identifies that a positive impact on safety outcomes was realised from employee perceptions of management's commitment to safety, colleagues participation in safety and the effectiveness of education and training efforts on the part of management.

Grimaldi and Simonds (1989) define the safety hierarchy within an organisation as firstly, the Chief Executive Officer (CEO), who is accountable for the safety demeanour of the organisation. Next, the safety person within an organisation is merely management's representative, who develops the information needed which enables the line to exercise its authority effectively in behalf of safety. Furthermore, the higher the safety specialist can reach in the organisation (eg. CEO) the greater effectiveness they will have with the lower echelons. Additionally, Grimaldi and Simonds (1989) identify the character traits of a successful safety director as knowledgeable, respected and persuasive. Moreover, Grimaldi and Simonds (1989) identified that generally safety specialists are more successful at encouraging safety consciousness rather than persuading safe behaviour. A contributing factor to this would be production performance versus safe behaviour trade-off.

In Table 2.1 the safety records within the automobile manufacturing industry are presented with relation to the size of the organisation, as well as the number of safety people in the organisation. From this table, one can infer

Table 2.1: Safety records in automobile industry (adapted from Grimaldi and Simonds (1989))

Employees	**Safety People**	**Safety Record**
140 - 580	0	15.7
400	1	2.3
11000	1	0.7
15000	6	1
18000	9	3.7

that organisations with permanent dedicated safety personnel, regardless of how many, have vastly better safety performance as opposed to organisations without dedicated safety personnel. Furthermore, the presence of at least one person continually promoting safety is far more significant than ratio of safety workers to number of employees. Despite the data in this table being old, the theory is still valid with respect to the conclusions portrayed, linking improved safety to permanent safety personnel.

In numerous larger organisations, there are entire departments devoted to safety. Grimaldi and Simonds (1989) state that these safety departments and safety personnel do not have the authority to shut down jobs and operations considered hazardous, however, they have to use their education and persuasion to get managers to discontinue unsafe acts. An operational conflict frequently exists concerning the necessity for safety and the preference to accept the decision based on cost-benefit considerations. Normally, safety directors merely have advisory power. Despite forthcoming dangerous situations being identified, the safety officer's decisions often inflict demands that threaten an operation's performance, which a manager is likely to resist. This is then resolved by higher authority and decided upon merits rather than on what is morally best.

Grimaldi and Simonds (1989) speculate that if safety specialists have the authority to shut operations down, this would give them great power over production managers, which commonly is not in line with organisational hierarchies. Thus the power of persuasion to influence necessary actions is valuable with the use of well marshalled relevant facts. Despite safety being everyone's responsibility, Grimaldi and Simonds (1989) find that most functions in modern society are fulfilled through an organisational hierarchy and thus the accountability for the safety of others increases in significance as the echelons are climbed.

Grimaldi and Simonds (1989) find that superior safety records are found in industries whose operations involve hazards that may possibly cause severe consequences (such as mining) rather than other industries whose work does not consist of such naturally inherent hazardous work. The motivation for implementing safety is intense when inherent hazards are evident and serious and as such, management often makes a very strong demand for safety achievements. Figure 2.1 depicts the result of bad risk management and how quickly matters escalate unless events come under control.

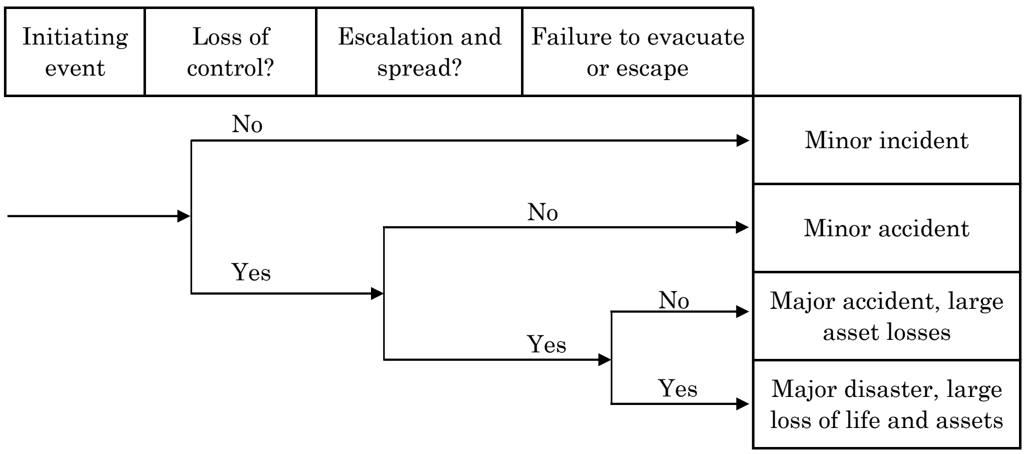


Figure 2.1: Result of bad risk management (adapted from Wong (2010))

From Figure 2.1, it can be seen that if an initiating event is not brought under control, quickly events can become out of control which could result in a possible major disaster. Whereas if well implemented risk management systems were in place, the consequences of the initiating event can be contained to a minor incident. Reasons people do not record all injuries and near misses are identified by Wong (2010) as the fear of blame culture, too much paperwork, a waste of time, lack of motivation and too busy to bother. However, Wong (2010) goes on to say that it is crucial to record all injuries and near misses, since persistent near misses could lead to an injury and thus a review of these persistent near misses can be done in order to prevent an injury from occurring in the future.

From personal correspondence with Turketti (2013), six mistakes are highlighted that managers tend to make with occupational health and safety. These mistakes are

- Not walking the talk
- Turning a blind eye
- Not giving enough positive feedback
- Not buying into the health and safety system
- Forgetting the importance of habits
- The wrong intentions for health and safety observations

Walking the talk – According to Turketti (2013), actions speak louder than words when it comes to occupational health and safety management. Furthermore, people tend to look to their manager for direction and their manager's conduct is an aspect they will notice. Thus a manager ought to reveal to everyone that ensuring people's health and safety is at the top of their priority list. As well as to remember that nothing makes a difference if employees see managers acting in a different way to what they are saying. Moreover, Wong (2010) agrees that management has to show strong leadership, "walk the walk" and "talk the talk" on the workshop floor to create a safety culture in an organisation.

Turning a blind eye – Health and safety rules and systems apply to everyone, permanently. If a manager were to overlook minor breaches or small unsafe acts and conditions, then they are effectively condoning and encouraging those actions. Thus, by the manager's personal absence of action they are indirectly informing their team that it is acceptable to not comply with certain rules or procedures.

Not giving enough positive feedback – It is important to give people positive feedback when found working healthy, safely or doing things that improve the workplace, rather than just letting people know when they are not working healthy, safely or following the correct procedures, although this is imperative too. Unfortunately managers tend to emphasise the negative more than the positive which can lead to disastrous consequences. If managers want the morale of the workforce to improve, they need to pay compliments where they are due and the culture will automatically improve towards a more positive health and safety climate.

Not buying into the health and safety system – Despite whether a manger likes or agrees with the health and safety system or not, managers in operation need to buy into the health and safety systems. If a manager has feedback about why they believe the system will not work, that feedback must be passed on to their boss and not to the employees under them. Furthermore, a team consists of the manager and his/her workforce (not the one or the other) and both need to be committed to the health and safety system to make it work and achieve its objectives. One person not buying into the management system can cause the entire team to fail.

Forgetting the importance of habits – Habits are what save people when their mind is not consciously on the job. Many health and safety systems used are aimed at generating habits in people's minds so that they are always cognisant of hazards in the work environment, as well as able to react when they see something that is about to hurt them. Repeating safety training or safety talks is most certainly not a waste of time or money because when a crisis hits it will probably be those repetitive safety sessions that will prevent great harm or loss.

The wrong intentions for health and safety observations – When partaking in health and safety observations, the aim should be to find ways to give employees constructive feedback which would keep them on their toes and challenge them in their work, not to try to catch people doing something wrong. It is imperative to challenge and test people to make sure they know what they are doing and how to do it correctly and safely.

2.2.2 Safety climate

All types of climates are based on an individual's perceptions of the practices, procedures and rewards in the organisation. A few of the organisational climates found are, a safety climate, climate for customer service and climate for innovation, etc. Wu *et al.* (2008) identify a safety climate as "employees perceptions of safety culture in the organisation; and the perceptions, which are influenced by the organisational factors and individual factors, eventually affect employees safety behaviours." Furthermore, Griffin and Neal (2000) confirm this with identifying that a safety climate should reflect perceptions of safety-related policies, procedures and rewards. Furthermore, the safety climate should reflect the degree to which employees believe that safety is valued within the organisation. Griffin and Neal (2000) go on to state that management's commitment to safety related matters (for example, managements concern for employee well-being, managements attitudes toward safety, perceptions that safety is important to management and production and safety trade-offs) is often included in a safety climate. Lastly, O'Toole (2002) states that the safety culture has been identified as a critical factor that sets the tone for importance of safety within an organisation.

Examples of fundamental safety undertakings that need to be carried out by individuals to sustain workplace safety are adhering to lockout procedures and wearing Personal Protective Equipment (PPE). These are the activities that make up organisational safety compliance as identified by Griffin and Neal (2000). Furthermore, Griffin and Neal (2000) state that safety participation describes behaviours such as partaking in voluntary safety activities or attending safety meetings. Although these behaviours may not directly contribute to workplace safety, they do cultivate an environment that supports safety.

Groves *et al.* (2007) found that manufacturing and mining employee's perceptions of safety climate were profoundly associated to employee's safety knowledge and the degree to which employees participate in safe work behaviours. Borodzicz (2007) identifies that some of the most pertinent and challenging risks to manage are often handled at a junior level within an organisation. When done constructively, there are noticeable links here that bring about a good 'safety culture' or 'risk culture' within the organisation by including more junior staff in the risk and security problems.

When analysing an accident, it should be similar to a systems analysis, where an accident is the undesired output of the system. Furthermore, Hoyos *et al.* (1988) identify that the system definition is essential, it must not be too extensive or constricted. For example, with a mine hauling accident, it would be insufficient to regard the driver and the means of transportation as the system and take no notice of those parts of the mine where transported goods are loaded and unloaded. From this, it is established that safety programs are required. Grimaldi and Simonds (1989) identify an overview of four basic steps all conventional safety programs should contain. These are as follows:

- ✧ **Case analysis:** Classify events triggering injuries, detect their origins, determine trends and evaluate these events.
- ✧ **Communication:** Communicate the knowledge derived from the case analysis.
- ✧ **Inspection:** Perform inspections to ensure people comply with injury counter measures and to detect unsafe conditions and practices before an injury occurs.
- ✧ **Supervisor safety training:** Orientate the supervisor about safety achievement responsibilities.

Grimaldi and Simonds (1989) go into more detail and identify seven steps that should be taken in the creation of a basic safety programme. These steps are as follows:

- ✧ **Secure principal managements involvement:** Obtain highly visible commitment to safety from management.
- ✧ **Organise for achievement:** Safety specialist is expected to marshal facts and resources, forming a coordinated effort.
- ✧ **Detail the operating plan:** The company's safety objective, policies, rules and regulations and the method chosen for their implementation should be communicated upon the programs initiation. All participants should be made aware of revisions as well.
- ✧ **Inspect operations:** Knowledge about the conditions to be corrected and an on-going evaluation of the progress being made is provided by plant inspections.

- **Consider engineering revisions:** Corrections are expected to begin with consideration of means of removing physical hazards.
- **Use guards and protective devices as a last resort:** If engineering revisions are not possible, or will not complete the safety objective, use supplementary means to safeguard the exposure.
- **Provide education and training:** Awareness and motivational development are necessary ingredients in the remedy for controllable injuries and illnesses.

2.2.3 Safety performance

Safety is defined by Van Steen (1996) as the absence of danger from which harm or loss could result. Thus the only manner to measure performance is in terms of harm or loss that occurs and consequently decreasing harm or losses indicates performance is improving. Shannon *et al.* (1997), Wu *et al.* (2008), and Grimaldi and Simonds (1989) identify that the most common measurement of safety performance is the injury/accident rate, although as Grimaldi and Simonds (1989) state, top management occasionally likes to measure safety performance as the costs saved from the safety efforts employed. Shannon *et al.* (1997) continue, that measuring safety performance in injury rates is convenient since all accidents of a certain severity level are obligated to be reported by law and the statistics has to be published to the public, which means there is readily available data. However, Van Steen (1996) believes that safety performance cannot be expressed in terms of a single parameter or index. Rather, they believe it is a range of mostly qualitative, but sometimes quantitative, indicators from each monitoring activity. The separate measurements can be expressed in a variety of ways. These ways include:

- Inferences based on, for example, the number and nature of defects or non-conformances found and the nature and type of recommendations made.
- Qualitative assessments of performance on broad scales from, say, 'poor' (immediate improvement action needed) through 'satisfactory' (capable of improvement) to 'good' (best practice, no action necessary).
- Quantitative ratings - for example, percentage compliance with the various specific elements of the management system.
- Quantitative and/or qualitative ratings about the quality of the safety management activities and about system implementation commensurate with the risks of the operations.

It was stated by Hoyos *et al.* (1988) that during the premature stages of industrialisation, sources of hazards were predominantly of a mechanical nature (eg. unprotected rotating wheels, exposed transmissions, etc.). Thus in general, the potential for danger was fairly apparent. In this day and age with modern technology, a lot of equipment is becoming electronic and the control of machines is being taken over by computers. As a consequence of this automation and mechanisation, more incidents transpire during the course of repair work as opposed to during the operation of the machines. Furthermore, Jansen and Brent (2005) stated in 2005 that the South African platinum mining industry had experienced a significant increase in fatal accidents. They go on to state that mine accidents are in principle preventable and there is enormous pressure on employers to reverse this trend.

Van Steen (1996) quotes that "you cannot manage what you do not measure". Van Steen (1996) goes on to identify that safety performance measurement covers four areas, three positive areas and one negative area. As can been seen in Figure 2.2, the three positive measurement areas are, plant and equipment, people and systems and procedures; the negative area measured is failures. Examples of each area are also presented in the figure.

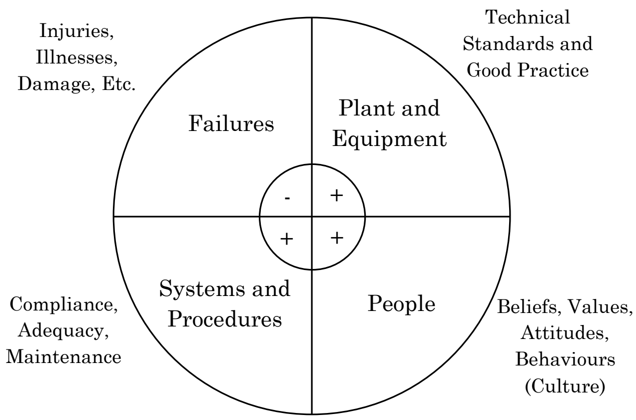


Figure 2.2: Safety performance measurement areas to be covered (adapted from Van Steen (1996))

Van Steen (1996) continues by stating that continual improvement in safety management tries to proactively develop the positive inputs and diminish the negative outputs, which will decrease the total incidents that create harm and loss to people, the environment and assets which can be seen in Figure 2.3. Safety management consists of three main areas, namely, the plant and equipment, people, and systems and procedures. The plant and equipment performance should reduce the risks from identified hazards as far as is reasonably practicable. The people must be competent through knowledge, skills and attitudes, to operate the plant and equipment and to implement the systems and procedures. The systems and procedures should operate and maintain the plant and equipment in a satisfactory manner and manage all associated activities. This control reduces risk of operations.

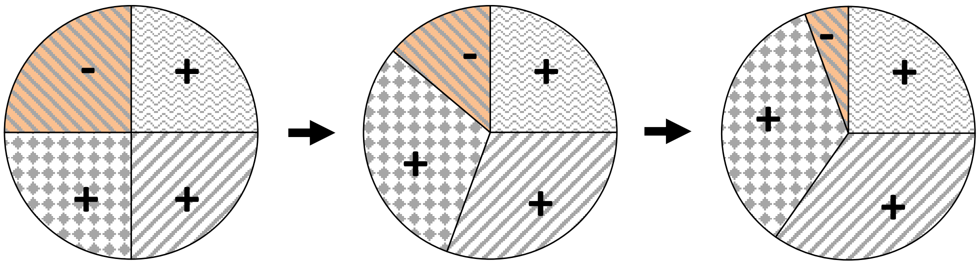


Figure 2.3: Safety performance continual improvement (adapted from Van Steen (1996))

Loubser (2010) brings about a different aspect to safety by introducing the fact that the notion of caring is in most cases, confused with material needs and not psychological needs. He goes on to say that by providing employees a job, most managers think that employees should be grateful and return the goodwill by being loyal, productive and working safely. In extreme cases, managers hold the view that employees should be fortunate to have a job. In order to show and demonstrate that management are caring for the safety of the workforce, management requires being involved, dedicated and committed. Lastly, Loubser (2010) identifies that the main drive of any organisation should be to attain the trust and respect of the workforce, because the secret of optimal safety performance lays within trust and respect.

Society generally accepts a risk probability of one in a million (10^{-6}) for a fatality to occur as completely acceptable as stated by Grimaldi and Simonds (1989). They go on to present several common exposures that relate to a fatality risk probability of 10^{-6}, these can be seen below:

- Smoking 1.4 cigarettes
- Traveling 16.1 km by bicycle
- Traveling 483 km by car
- Traveling 1610 km by jet
- Having one chest x-ray
- Living five years at a site boundary of a typical nuclear power plant in the open
- Drinking thirty 340 g cans of diet soda

The size of an organisation does play a role in the safety performance, as highlighted by Grimaldi and Simonds (1989). They identify that organisations with a small number of employees (50 - 500) have higher injury frequency rates compared to those with masses of employees (over 2000). The injury frequency rates can be seen in Table 2.2.

There are two types of injury frequency rates, the first being Lost Time Injury Frequency Rate (LTIFR) and the second being Fatal Injury Frequency

Table 2.2: Work injury rates rated by establishment size (adapted from Grimaldi and Simonds (1989))

Employees	**Injury frequency rate**
Less than 20	9.9
20 to 49	13.4
50 to 99	17.0
100 to 249	20.4
250 to 499	17.9
500 to 999	14.2
1000 to 2499	11.2
2500 or more	7.3

Rate (FIFR). They are both calculated in the same manner, however, the LTIFR uses the number of accidents that resulted in a LTI (i.e. An injury that results in workers being unable to report to their next work shift (Talisman, 2014)). Then the FIFR makes use of the number of accidents that resulted in a fatality (i.e. an employee died from the accident). Generally, the LTIFR and FIFR are presented per million man hours at work. The LTIFR and FIFR calculations are taken from Wannenburg (2011) and presented in Equations 2.2.1 and 2.2.2.

$$\mathrm{LTIFR} = \frac{\mathrm{LTI} \times 1000000}{E \times H} \tag{2.2.1}$$

where:

LTIFR is Lost Time Injury Frequency Rate (per million man-hours)

LTI is Number of Lost Time Injuries

E is Number of Employees

H is Hours per Employee per Anum

$$\mathrm{FIFR} = \frac{\mathrm{FI} \times 1000000}{E \times H} \tag{2.2.2}$$

where:

FIFR is Fatal Injury Frequency Rate (per million man-hours)

FI is Number of Fatal Injuries

E is Number of Employees

H is Hours per Employee per Anum

Industry in general uses the LTIFR and FIFR as safety performance measures, although other measures do exist. Table 2.3 displays injuries in the South African mining industry over the period from 2008 until 2012, which are grouped according to commodity[2]. One can easily identify that gold, platinum and coal are the three highest contributors to South African mining accidents.

Table 2.3: Number of mining injuries by commodity in South Africa (adapted from South African Department of Mineral Resources (2013*d*), South African Department of Mineral Resources (2013*e*), South African Department of Mineral Resources (2013*f*) and South African Department of Mineral Resources (2013*g*))

	Injuries				
Commodity	**2008**	**2009**	**2010**	**2011**	**2012**
All Mines	3750	3650	3438	3299	3377
Gold	1938	1756	1379	1498	1478
Platinum	1221	1299	1515	1283	1360
Coal	332	295	273	241	267
Diamonds	35	46	50	42	48
Copper	22	19	19	19	13
Chrome	58	60	84	71	77
Iron Ore	12	15	18	20	20
Manganese	16	11	17	13	15
Other	116	149	82	112	99

From Table 2.3, the top three contributors to accidents are plotted to easily identify the current accident trends, as can be seen in Figure 2.4. The first critical observation is that from 2011 to 2012 the number of accidents increased.

Figure 2.5 zooms into 2012, graphically presenting the percentage split of accidents across all the commodities. Again, it is clear that gold and platinum mines are the largest contributors to South African mining accidents.

[2] In 2010 there is one more accident in total than in the sum of the nine commodities, it is unsure were the error is, however, this is as it is reported in the South African Department of Mineral Resources (2013*f*) Annual Report: 2011 - 2012.

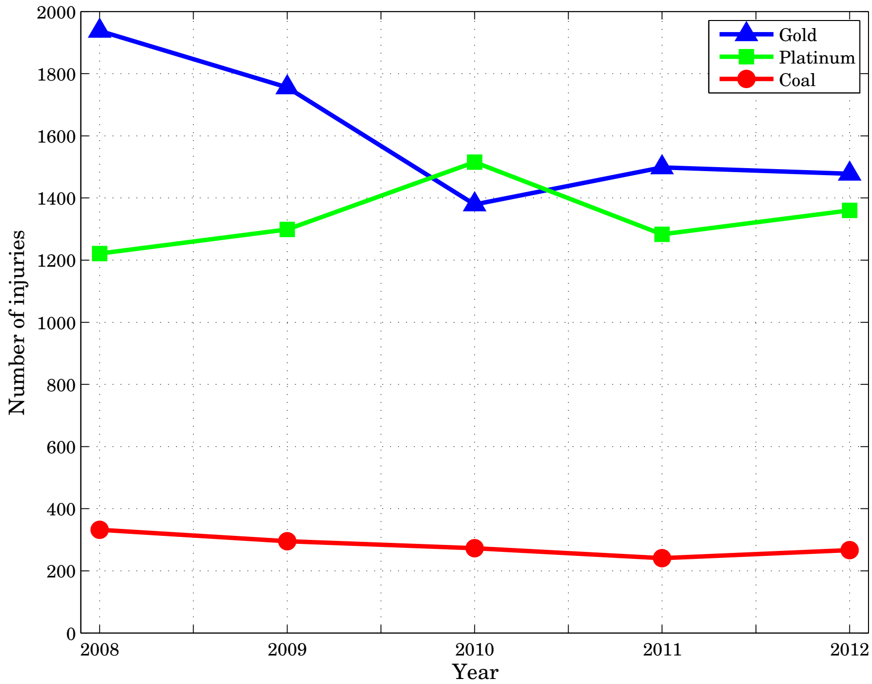


Figure 2.4: South African mining injuries from 2008 to 2012 (adapted from (South African Department of Mineral Resources (2013*d*), South African Department of Mineral Resources (2013*e*), South African Department of Mineral Resources (2013*f*), and South African Department of Mineral Resources (2013*g*)))

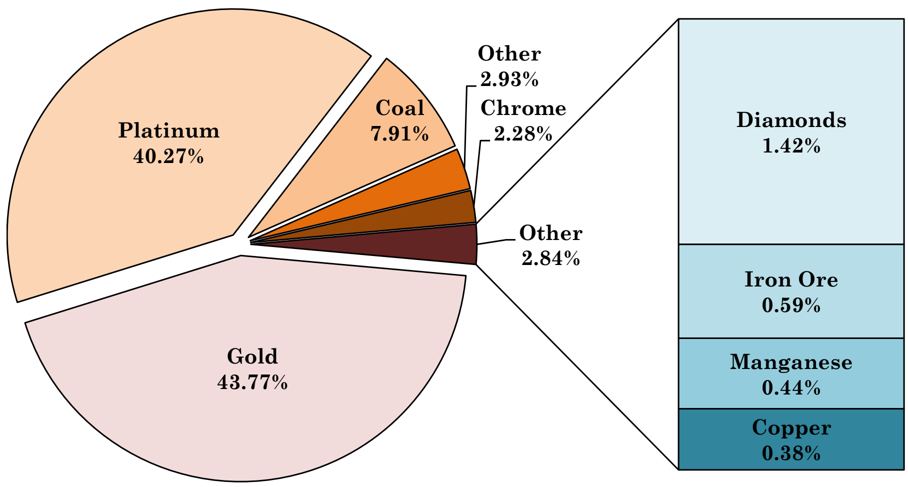


Figure 2.5: South African mining injuries in 2012 by commodity (adapted from (South African Department of Mineral Resources (2013*d*), South African Department of Mineral Resources (2013*e*), South African Department of Mineral Resources (2013*f*), and South African Department of Mineral Resources (2013*g*)))

2.2.4 Safety leadership, climate, and performance relationship

Loubser (2010) identifies that safety inspections and audits repeatedly reveal that managers and supervisors are unsuccessful at conforming with their safety risk control responsibilities without suffering any negative consequences. Additionally, non-compliances with safety risk control responsibilities are evidence of non-caring behaviours and non-caring behaviours have a substantial influence on the safety performance of employees. Furthermore, Loubser (2010) states that non-caring is the core cause for forming a 'mind my own business' safety culture and thus a non-caring safety culture encourages risk taking behaviour which is gambling with one's own safety and the safety of others.

Hofmann and Tetrick (2003) define four types of leadership along with how they fit in with an organisations safety climate and its leadership, as can be seen in Figure 2.6. The four leadership types are, transformational, constructive, corrective and laissez-faire. Transformational leadership is value-based and personalised communication, resulting in better discussion quality and a larger concern for welfare. Constructive leadership entails an intermediate level of concern for an employee's welfare. Corrective leadership primarily embraces error detection and correction based on active or passive monitoring. Laissez-faire leadership offers the lowest level of concern for welfare.

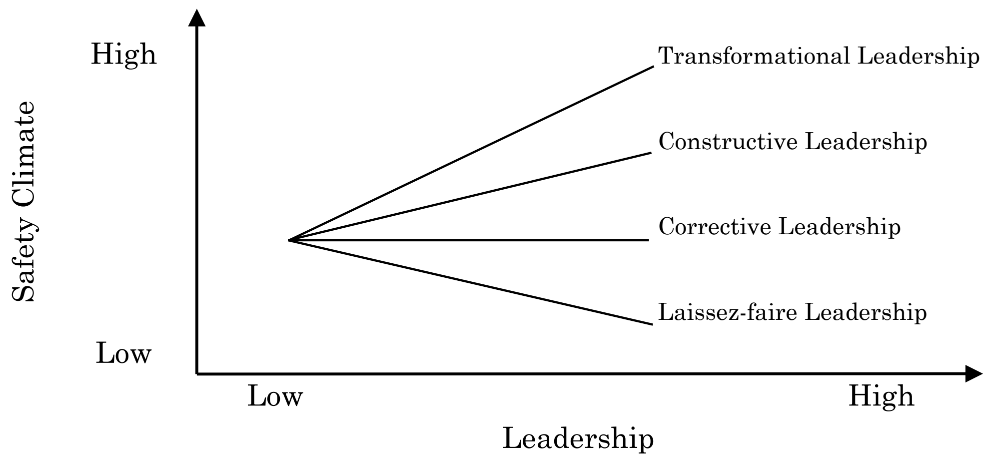


Figure 2.6: Relationship between leadership and safety climate (adapted from Hofmann and Tetrick (2003))

Wu *et al.* (2008) state that the better an organisation's safety climate, the better its safety performance. Furthermore, employees who perceive their job as safe tend to be involved in less accidents than employees who perceive their job as dangerous. Additionally, Wu *et al.* (2008) identify a significant positive correlation between safety climate and safety performance through research performed. In their research, four hypotheses were tested of which all four were supported. The four hypotheses are as follows:

- ✧ Safety climate mediates the relationship between safety leadership and safety performance. This hypothesis means that safety climate has a direct effect on safety performance and safety leadership has an indirect effect on safety performance.
- ✧ Safety leadership is positively related to safety climate. This hypothesis means that the more positive the perceived safety leadership, the more positive the perceived safety climate.
- ✧ Safety climate is positively related to safety performance. This hypothesis means that the more positive the perceived safety climate, the more positive the perceived safety performance.
- ✧ Safety leadership is positively related to safety performance. This hypothesis means that the more positive the perceived safety leadership, the more positive the perceived safety performance.

Figure 2.7 is used by Wu *et al.* (2008) in their research to aid in creating an operational definition of safety leadership, climate, and performance. The operational definition is a score from all the dimensions under each section seen in the figure.

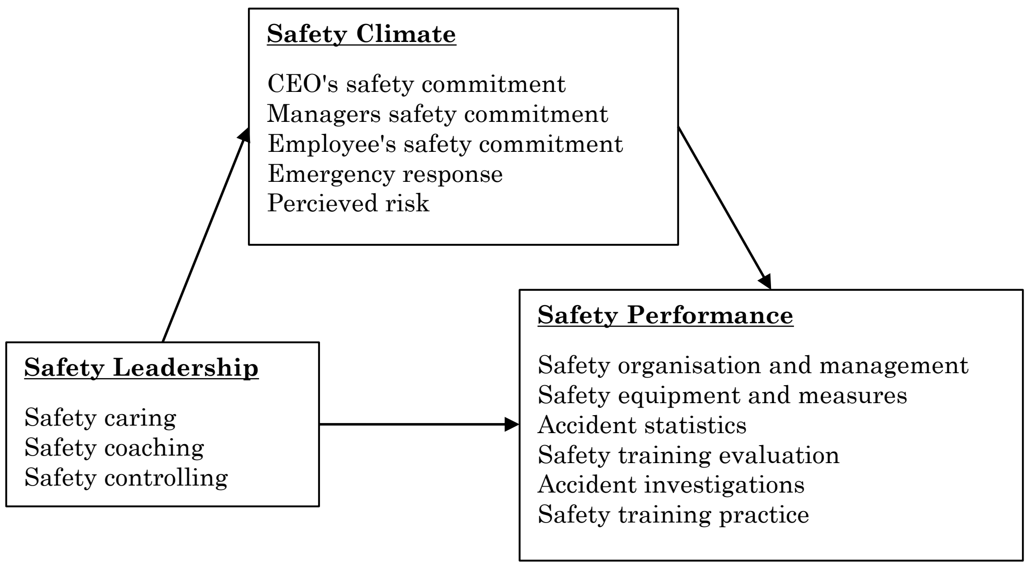


Figure 2.7: Model relating safety leadership, safety climate, and safety performance (adapted from Wu *et al.* (2008))

The practical application of the study performed by Wu *et al.* (2008) expresses that safety leadership and safety culture are two vital forecasters of a good safety performance and that safety climate takes a mediating role in the relationship between safety leadership and safety performance.

2.2.5 Safety models

Hoyos *et al.* (1988) deliberate that all knowledge with respect to how accidents take place, as well as all facts about safe and unsafe conduct at work, eventually must be converted into processes which protect the obligatory jobs and improve the safety of socio-technical systems. Leveson (2004) goes on to provide a solution for Hoyos *et al.* (1988) by introducing that accident models form the foundation for investigating and analysing accidents, preventing future accidents and determining whether systems are suitable for use, such as for a risk assessment. Maiti and Bhattacherjee (2001) add that accident researchers should extend the study of individual characteristics to include the work-environmental factors which may affect the risk of injury too. Furthermore, Hoyos *et al.* (1988) add that risk estimation techniques serve to evaluate the level of risk involved in the operation and detailed analysis of the actual single incidents and accidents by means of models is typically employed to identify possible weak spots in the plant and its operation.

Hoyos *et al.* (1988) define direct and indirect as the two core approaches used when dealing with hazard and safety analysis methods. Direct encompasses detecting accident potentials in planned or present systems. Indirect includes comprehensive studies and statistical analyses of accidents. Despite these two core tactics, there are a host of different types of models, some such models are causal, probabilistic, statistical, epidemiological, hazard identification and analytical trees, as identified by Hoyos *et al.* (1988). Hoyos *et al.* (1988) continue that causal or probabilistic models can predict the level of risk involved in a process in structured work areas with single incidents occurring (some examples include Fault Tree Analysis (FTA), Management Oversight & Risk Tree (MORT) and National Institute for Research & Safety model (INRS)). However, for circumstances characterised by less structured work and a relatively high number of incidents reported (such as workshops and construction sites), alternate methods are employed, such as statistical and epidemiological methods. Furthermore, Hoyos *et al.* (1988) list a few models, Failure Modes & Effects Analysis (FMEA), Preliminary Hazard Analysis (PHA), Failure Modes, Effects & Criticality Analysis (FMECA) and Systems Hazard Analysis (SHA) that all fall under the heading of hazard identification models and FTA and MORT fall under the heading of analytical trees which are used in safety analysis.

As can be seen in Table 2.4, Lehto and Salvendy (1991) present a large comparison of 64 different accident causation models.

Table 2.4: Accident causation models comparison (adapted from Lehto and Salvendy (1991)

			Area			Purpose				Focus				Structure				Input			Output				
			Industrial	Transportation	Generic	Descriptive	Prescriptive	Generic	Specific	Human	Process	Task	Accident	Mathematical	Verbal	Logical	Sequential	Definitions	Specifications	Nothing	Hazards	Errors	Probabilities	Causes	Solutions
General Models of the Accident Process	Sequential Models	Domino Theory	✗			✗		✗		✗			✗		✗		✗			✗				✗	
		Updated Domino Theory	✗			✗		✗		✗	✗	✗	✗		✗		✗			✗				✗	
		Stair Step Model	✗			✗		✗		✗	✗	✗	✗		✗		✗			✗				✗	
		Stage Model		✗		✗			✗	✗		✗	✗	✗	✗		✗		✗				✗	✗	
		Event Trees			✗	✗		✗					✗	✗		✗	✗	✗	✗		✗		✗	✗	
		Fault Trees			✗	✗		✗			✗		✗	✗		✗	✗	✗	✗		✗		✗	✗	
		Cause Trees			✗	✗		✗		✗	✗		✗			✗	✗	✗	✗		✗		✗	✗	
		MORT	✗			✗	✗		✗	✗	✗	✗	✗		✗	✗	✗	✗	✗		✗	✗		✗	✗
		Multi-linear Sequencing			✗	✗		✗			✗		✗				✗	✗	✗		✗			✗	
		PERT/CPM			✗	✗		✗			✗		✗	✗			✗	✗	✗		✗		✗	✗	
	Epidemiological Models	Host-Agent-Environment			✗	✗		✗		✗	✗	✗			✗			✗						✗	
		Cohort Analysis			✗	✗		✗		✗	✗	✗			✗			✗						✗	
		Home Accident Model				✗			✗	✗	✗	✗	✗		✗		✗			✗				✗	
		Industrial Accient Model	✗			✗			✗	✗	✗	✗	✗		✗		✗			✗				✗	
		Haddon Matrix		✗		✗			✗	✗	✗	✗	✗		✗		✗			✗				✗	
	Energy Transfer Model	Energy Exchange Model			✗	✗		✗		✗	✗		✗		✗			✗	✗		✗			✗	
		Energy Countermeasures			✗	✗		✗		✗	✗		✗		✗			✗	✗		✗			✗	✗
	Systems Models	P-Theory			✗	✗		✗					✗		✗			✗	✗		✗			✗	
		Change Analysis	✗		✗	✗	✗	✗		✗	✗	✗	✗		✗			✗	✗		✗	✗		✗	✗
		Manual Control Theory		✗	✗	✗		✗		✗		✗		✗				✗	✗			✗		✗	
		Car-Driver Model		✗		✗			✗	✗	✗	✗		✗						✗		✗		✗	✗
Models of Human Error and Unsafe Behaviour	Behavioural Accident Models	Accident Proneness			✗	✗			✗	✗					✗					✗				✗	
		Personality Traits			✗	✗			✗	✗					✗				✗					✗	
		Life Change Units			✗	✗			✗	✗				✗	✗				✗					✗	
		Adjustement Stress Theory			✗	✗		✗		✗		✗			✗					✗				✗	
	Human Decision Making Models	Purposive Risk Taking Model		✗		✗		✗	✗		✗				✗					✗		✗		✗	
		Risk Perception Model			✗	✗			✗	✗				✗	✗				✗			✗		✗	✗
		Risk Acceptability Model			✗	✗			✗	✗				✗	✗				✗			✗		✗	✗
		Heuristic and Biases			✗	✗		✗	✗						✗					✗		✗		✗	
		Expected Utility			✗	✗		✗	✗	✗				✗	✗				✗			✗		✗	✗
		Signal Detection			✗	✗		✗		✗	✗			✗	✗				✗			✗	✗	✗	✗
		Bayesian Inference			✗	✗		✗	✗	✗	✗			✗	✗		✗		✗			✗	✗	✗	✗
		Brunswick Lens			✗	✗		✗	✗	✗	✗			✗	✗				✗			✗	✗	✗	✗
	Human Information Processing Models	Single Channel Hypothesis			✗	✗		✗		✗		✗			✗		✗		✗			✗		✗	✗
		Human Error Model			✗	✗		✗		✗		✗	✗		✗		✗		✗			✗		✗	
		Decision Stage Model			✗	✗		✗		✗		✗	✗		✗		✗		✗		✗	✗		✗	
		Communication Model			✗	✗		✗		✗		✗			✗		✗		✗			✗		✗	
		Warning Tree			✗	✗		✗		✗		✗	✗		✗	✗	✗		✗		✗	✗	✗	✗	
		Arousal/Effect/Attention			✗	✗		✗		✗		✗			✗		✗		✗			✗		✗	✗
		Resource Allocation			✗	✗		✗		✗		✗			✗		✗		✗			✗		✗	✗
		Task Scheduling			✗	✗		✗		✗		✗		✗	✗	✗	✗		✗			✗		✗	✗
		Levels of Performance			✗	✗		✗		✗		✗			✗		✗		✗			✗		✗	✗
		GOMS			✗	✗	✗	✗		✗	✗	✗			✗	✗	✗	✗	✗			✗		✗	✗
	Human Error Taxonomies	Data Store	✗			✗			✗	✗		✗		✗					✗			✗	✗		
		Error Mechanisms			✗	✗		✗		✗		✗			✗					✗		✗		✗	
		Integrative Taxonomy	✗			✗		✗		✗	✗	✗			✗				✗			✗		✗	

Table 2.4: Accident causation models comparison (adapted from Lehto and Salvendy (1991)

		Area			Purpose				Focus				Structure				Input			Output				
		Industrial	Transportation	Generic	Descriptive	Prescriptive	Generic	Specific	Human	Process	Task	Accident	Mathematical	Verbal	Logical	Sequential	Definitions	Specifications	Nothing	Hazards	Errors	Probabilities	Causes	Solutions
Models of the Mechanics of Human Injury	Tool Use Trauma	✗			✗	✗		✗	✗	✗	✗	✗		✗				✗		✗			✗	✗
	CTD-123	✗			✗	✗		✗	✗	✗	✗	✗	✗	✗				✗		✗		✗	✗	✗
	NIOSH Lifting Guide	✗			✗	✗		✗	✗	✗	✗	✗	✗	✗				✗		✗			✗	✗
	Biomechanical Model	✗		✗	✗	✗		✗	✗	✗	✗	✗	✗	✗				✗		✗			✗	✗
	MMH Mode	✗			✗	✗		✗	✗	✗	✗	✗	✗	✗				✗		✗			✗	✗
	Slip Resistance	✗		✗	✗	✗		✗	✗	✗	✗	✗	✗	✗				✗		✗			✗	✗
	Ladder Climbing	✗		✗	✗	✗		✗	✗	✗	✗	✗	✗	✗				✗		✗			✗	✗
Application Techniques	Fault Tree Analysis	✗		✗	✗		✗			✗		✗	✗		✗	✗	✗	✗		✗		✗	✗	
	FMEA	✗		✗	✗	✗	✗			✗		✗	✗		✗	✗	✗	✗		✗		✗	✗	✗
	HAZOP	✗		✗	✗	✗	✗			✗		✗		✗		✗	✗	✗		✗		✗	✗	✗
	STARS	✗		✗	✗	✗	✗			✗		✗		✗	✗	✗	✗	✗		✗		✗	✗	✗
	WSA	✗			✗	✗	✗		✗		✗	✗		✗		✗	✗	✗		✗	✗	✗	✗	✗
	AEA	✗			✗	✗	✗		✗		✗	✗		✗		✗	✗	✗		✗	✗	✗	✗	✗
	Decision Sequence Analysis		✗		✗		✗		✗		✗	✗		✗		✗	✗	✗			✗	✗	✗	✗
	D/R/C matrix	✗			✗		✗		✗	✗	✗	✗		✗			✗	✗			✗			
	THERP	✗			✗			✗	✗	✗	✗		✗		✗	✗		✗			✗	✗		
	SLIM-MAUD	✗			✗		✗		✗	✗	✗		✗	✗			✗	✗			✗	✗	✗	
	SHERPA	✗			✗	✗	✗		✗	✗	✗			✗	✗	✗	✗	✗			✗		✗	✗

As can be seen in Table 2.4, all 64 models are distributed into four focal groupings. These are, general models of the accident process, models of human error and unsafe behaviour, models of the mechanics of human injury and application techniques. Additionally, these models are compared in six areas, these areas are, area, purpose, focus, structure, input and output. If one filters these 64 models to search for models that are generic for the area and purpose, focus on accidents, are mathematical in structure, have definitions and specifications as the inputs as well as outputs a probability, then this results in five usable models, which are, Event Trees (ET), Fault Trees (FT), Program Evaluation & Review Technique - Critical Path Method (PERT/CPM), Fault Tree Analysis (FTA), and Failure Modes & Effects Analysis (FMEA). The first three fall under sequential models, in the category of general models of the accident process and the last two fall under the application techniques section.

Leveson (2004) identifies that event-based accident models describe accidents in terms of multiple events sequenced as a chain over time, this can be in a forward sequence (such as FMEA or ET) or backward sequence (such as FT). Additionally Leveson (2004) finds that event-based models are bad at representing systemic accident factors, such as structural deficiencies in the organisation, management deficiencies and flaws in the safety culture of the company or industry. Leveson (2004) goes on to state that in event-based models, the causal factors identified depend on the events that are considered and the selection of the conditions related to those events. However, other than the physical events directly preceding or directly involving the accident, the choice of events to incorporate is subjective and the selection of conditions to explain the events are even more so. Although the first event in the chain is often labelled the "initiating event", the choosing of an initiating event is arbitrary and prior events and conditions could always be added. From this, the above list of five possible models is reduced to one model, which is the PERT/CPM. However, PERT/CPM is used primarily in project management, to identify the minimum time needed to complete a project, and it is more of an event-orientated technique. Thus, all five models mentioned are not suitable for this study.

According to Hovden *et al.* (2010) the majority of accident models and philosophies applied in the arena of occupational accidents are grounded on epidemiological models of energy-barriers and use a closed system safety mentality. From this, four contending modelling approaches developed. These are:

- ✧ Causal sequences similar to the domino model (e.g. International Loss Control Institute causation model (ILCI))
- ✧ Descriptive models of accident processes in terms of chronologically timed events and/or phases (e.g. Sequentially Timed Events Plotting (STEP) and Occupational Accident Research Unit deviation model (OARU))
- ✧ System models based on a combination of causal sequences and epidemiological models (e.g. TRIPOD and 'Swiss cheese' model)
- ✧ Logical risk analysis stimulated models (e.g. MORT and Safety Management and Organisation Review Technique (SMORT))

Hovden *et al.* (2010) continue that accident models can be used in both reactive and proactive safety management. However, he highlights that two systemic models were recently introduced which may stimulate a more creative quest for alternate and proactive safety performance indicators. These two models are Functional Resonance Accident Model (FRAM) and Systems-Theoretic Accident Model & Processes (STAMP).

Leveson (2004) explains that in STAMP, systems are regarded as interrelated components, held in a state of equilibrium by feedback loops of information and control. The process building up to an accident is defined in terms of an adaptive feedback function that does not succeed in maintaining safety, as performance fluctuates over time, to achieve a complex set of goals and values. Rather than describing safety management in terms of preventing component failure events, it is defined as a continuous control task to impose the constraints necessary to limit system behaviour to safe changes and adaptations. Thus, accidents can be understood, in terms of why the controls that were in place did not prevent or detect changes, by recognising the safety constraints that were violated and determining why the controls were inadequate in enforcing them.

Hollnagel (2014) states that the understanding of the role that humans play in accidents has gone through three phases. Firstly, humans are perceived to be susceptible to errors. The accident investigation purpose was therefore to identify the *human error* that either was the primary cause or the initiating event. Next, the *human error* view was not plausible and therefore, descriptions transformed to search for how performance shaping factors or performance conditions could *force* individuals to fail. This did not eliminate the notion of a *human error* but altered it from being an inherent human *error mechanism* to a result of working conditions and work pressures. Lastly, the human role in accidents was understood such that failures and successes have the same foundation. Hollnagel (2014) continues that FRAM offers an approach to describe outcomes using the idea of resonance arising from the unpredictability of daily performance. Furthermore, a FRAM can be used to obtain a description of functional variability and resonance, which can lead to recommendations for damping unwanted variability. A FRAM analysis consists of four main stages, which are:

- Identify and describe critical system functions and characterise each function using the six basic characteristics (Output, Input, Precondition, Resource, Control and Time).

- Characterise the potential variability of the functions in the FRAM model, as well as the possible actual variability of the functions in one or more instances of the model.

- Define the functional resonance based on dependencies/couplings among functions and the potential for functional variability.

- Identify ways to monitor the development of resonance either to reduce variability that may lead to undesirable consequences or to intensify variability that might lead to desired outcomes.

Lastly, the FRAM is a qualitative method which in its current version does not support quantification, although quantification is not impossible. However, a different nature for the quantification would be needed, since the FRAM concentrates on the prospect of function variability rather than the probability of malfunctioning or failure.

Tomas' Structural Equation Model (SEM), shown in Figure 2.8, is described by Attwood *et al.* (2006) as a model which suggests that accidents ought to be handled as if they had stemmed from an intricate sequence of events. Attwood *et al.* (2006) go on to identify the five conclusions identified from Tomas' SEM, which are:

- There is a significant explanatory chain that flows from safety climate through supervisors, co-workers and worker attitudes and behaviours to an accident occurrence.

- Safety climate does not have a significant direct effect on either safety behaviour or co-worker response.

- ✧ Supervisor response significantly affects co-workers' response, attitude and safety behaviour.
- ✧ Attitudes affect behaviour, while behaviour influences the probability of accidents occurring.
- ✧ Hazards do not have a direct impact on accidents (i.e. most hazards can be dealt with effectively if the workforce is both capable and motivated).

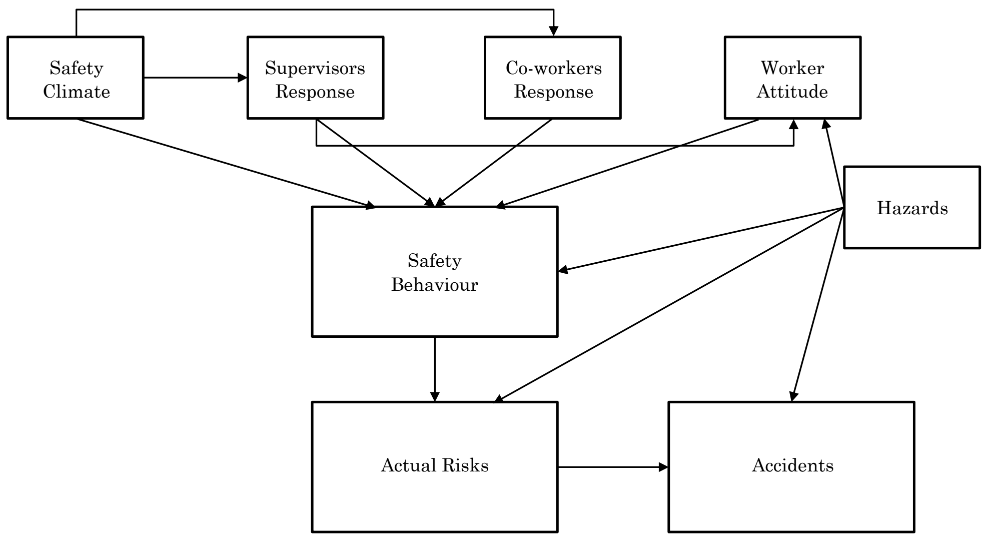


Figure 2.8: Tomas' Structural Equation Model (SEM) (adapted from Attwood *et al.* (2006))

2.3 Risks

Joughin (2011) identifies that in all areas of life, individuals need to comprehend that every action gives rise to risk and in the absence of risk nothing can be done. As such, it is not possible to achieve a state of zero risk, for the reason that a state of zero risk does not exist. Thus, decisions are required to be made on the tolerable levels of risk in industry. Furthermore, Hoyos *et al.* (1988) add to this by stating that a hazardous situation is developed due to the presence of potentially harmful energy. For example, a heavy moving truck is an obvious one, however a banana peel on the floor is not as obvious, yet it has the potential for one to step on and slip and injur themself. In addition to this, Wong (2010) states that nothing can be 100% reliable and safe. He identifies that reliability cannot be predicted without statistical data and that making things safe and reliable costs money. Furthermore, when everything operates without incident, operators and management may perhaps be comforted into a false sense of security and may do something dangerous. Ultimately, humans will make mistakes. Equally important, Hovden *et al.* (2010) identify that in the majority of industrial sectors the potential for attaining low injury rates through continuous work to improve performance through deviation control is high.

Borodzicz (2007), HSE (1997), and Hoyos *et al.* (1988) all agree that risk analysis is seen primarily in quantitative terms, by placing an assessment value on the combination of the frequency or probability of a potential physical failure and its severity. This approach leads to management apprehensions about how best to avoid, eradicate or diminish potential threats as well as aid in decision making about the costs and benefits of risk management. Risk tolerability is explained by Grimaldi and Simonds (1989), were it is identified that hazards are preferably eliminated or neutralised by fail safe methods so that no danger is present, however, this does not work in practice. The tolerability of the risk imposed after the application of the most effective controls practicable, governs the hazard's acceptability. Risk tolerability generally is determined as a combination of the seriousness of the effects and the likelihood of the undesirable event. Furthermore, occasionally, sensitivity of exposure is included in the combination too (for example, ethical and legal responsibility).

At the same time, Joughin (2011) adds to this argument by presenting the fatality guidelines developed in the United Kingdom (UK) for major industrial hazards in the form of an F-N diagram as can be seen in Figure 2.9. In this figure, N denotes the number of fatalities in a single event, and F denotes the frequency of occurrence of N or more fatalities in a year. This figure encloses three regions, the negligible region, the As Low As Reasonably Practicable (ALARP) region, and the intolerable region, furthermore, three lines are superimposed on the figure which identify what the Netherlands legislation, UK Health & Safety Executive and Hong Kong upper risk guidelines perceive and declare as their tolerable limit.

Webber-Youngman and Van Wyk (2013) ascertain that it is confirmed that fatalities are cyclical in nature, that there are periods of high fatality rates followed by periods of lower fatality rates, which is often due to concentrated devotion to improve adherence to safety standards, especially during the periods of higher fatality rates. However, in endeavouring to make a meaningful strive towards zero harm, the aim should be to minimise these cyclical tendencies. Regularly automation is identified as a method to avoid the human-hazard interactions, however, Hovden *et al.* (2010) consider that automation is not necessarily the approach to take. To illustrate this point, take the case study of occupational accidents and costs in the Norwegian furniture industry reported by Hovden *et al.* (2010). This case study revealed that automation of the production line reduced the number of injuries, especially the cutting of fingers, but it also revealed that maintenance and handling of disruptions resulted in more severe injuries, such as the amputation of arms.

Hoyos *et al.* (1988) present that the likelihood of a man-machine system being a success or failure is a combination of human reliability and equipment reliability. Human behaviour is difficult to define. Figure 2.8 presented by

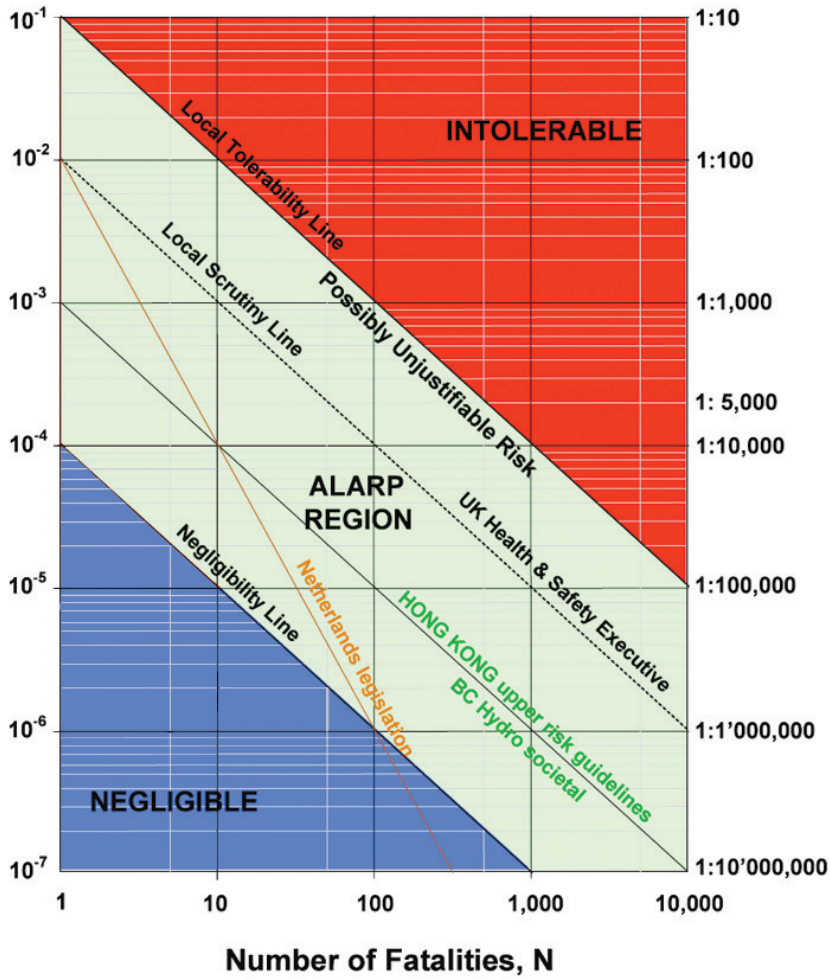


Figure 2.9: F-N diagram (adapted from Joughin (2011))

Attwood *et al.* (2006) of Tomas' SEM identifies some associations to a humans behaviour. Hovden *et al.* (2010) give some insight by stating that humans have the inclination to underestimate known risks and overvalue new risks. Moreover, Hofmann and Tetrick (2003) add to this insight by stating that job diversity may potentially alleviate boredom and improve attentiveness, thereby reducing risks, whereas excess job demands may cause workers to take shortcuts, thereby increasing the possibility of injuries. Luckily, equipment reliability is more defined. Equipment reliability can be divided into six types of failure probabilities, which is presented by PRAGMA (2013). These six types are presented in Figure 2.10 and they are, worst old, bathtub, slow aging, best new, constant and worst new. The first three contribute to 11% of equipment failures, while the last three take up the remaining 89% of equipment failures. Furthermore, the first three are generally more common in mechanical systems, while the last three are generally more common in electrical systems.

The 'Worst Old' case is the least common failure mechanism and an example of this type of system would include impellers, crusher jaws, tracks and liners. The 'Bathtub' case is a combination of 'Worst New' and 'Worst Old'

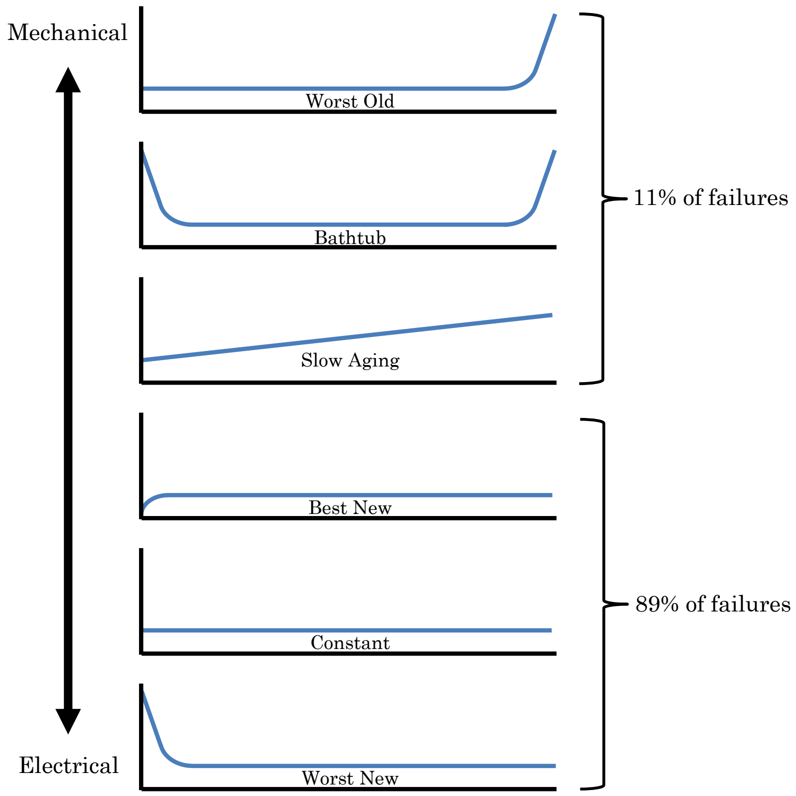


Figure 2.10: Six classes of equipment failure probability (adapted from PRAGMA (2013))

cases. It has a high probability of failure at the beginning and end of its life and an example of this case is a simple electromechanical system. The 'Slow Aging' case is a steady increase of probability of failure with age. It is generally associated with corrosion or creep and an example includes pipes, tyres and clutches. The 'Best New' case is not age related, except for the beginning of the equipment's life, an example would be hydraulics or pneumatics. The 'Constant' case is not age related, it is just random failure that is generally associated with complex equipment systems, a light bulb is an example of this equipment failure type. Lastly, the 'Worst New' case is the most common failure mechanism for complex equipment, an example would be electronics and avionics. Knowing these different failure modes for different types of equipment helps with knowing when to perform maintenance or perform condition monitoring to prevent unplanned equipment failure, which can place an operator in danger.

Jansen and Brent (2005) identify that hazards and risks inflicted on workers safety and well-being should be identified and evaluated on a continuous basis. From a combination of Jansen and Brent (2005) and Hoyos *et al.* (1988), a priority order of preventative and proactive measures that should be implemented are identified and ranked in order of efficiency of accident prevention, as listed below:

- ✧ Elimination of the hazard/risk
- ✧ Control of the hazard/risk at source and separation of the hazard and man
- ✧ Minimise the risk/hazard by the design of safe work systems
- ✧ Personal and technical protection
- ✧ Safety psychology

Statistically, South Africa has far higher road accidents than the UK and United States of America (USA). Joughin (2011) concludes that this is due to the South African culture not being risk averse. This willingness to take risks is also problematic in the South African mining industry. Furthermore, Webber-Youngman and Van Wyk (2013) identify that in the setting of the South African mining industry with its diverse workforce, it becomes a very serious challenge to ensure that every person that is exposed to risks comprehends the consequences of unsafe actions. This is due to the fact that South Africa has a multi-cultural and multi-lingual environment where the language can perhaps be a risk as well, as such the meaning of different risks and the prevention and or dealing with them can be understood differently by unalike linguistic groups. This in itself is a major risk, as one can never be sure that the equivalent message was heard by all as it was intended. Lastly, Jansen and Brent (2005) add that despite the mining industry growing and consequently facing the risks associated with greater than before mining depths, as well as extended tramming distances, of which this expansion is critical for employment and economic growth in South Africa, it cannot be completed at the expense of health and safety.

The South African Department of Mineral Resources (2013*g*) divide fatalities by classification, these classifications can be perceived as the risks associated with mining, they can be seen in Table 2.5. Understandably, the risk percentages for injuries and fatalities may differ, but they all bring a certain amount of risk into the mining industry. Wannenburg (2011) adds that these risks also vary between underground deep (underground operation with shafts more than 1000 m in depth) and underground shallow (underground operation with shafts less than 1000 m in depth) mines, however underground shallow and surface mines (which includes open-cast operations, surface complement at underground mines, as well as processing plants) contain similar risks.

According to the research of Groves *et al.* (2007), the six main causes of injuries in the mining industry are, handling material, slip or fall of person, machinery, hand tools, fall of roof and powered haulage. The six main causes of fatalities in mining is power haulage, machinery, fall of roof, slip or fall of person, electrical and fall of face. Rupprecht (2011) adds to this by associating transportation to 26% of all mine accidents in South Africa, which includes vertical (e.g. shaft), horizontal (e.g. haulages) and in-stope transportation

Table 2.5: South African mining fatalities per risk classification (adapted from South African Department of Mineral Resources (2013*d*), South African Department of Mineral Resources (2013*e*), South African Department of Mineral Resources (2013*f*) and South African Department of Mineral Resources (2013*g*))

Classification	2008	2009	2010	2011	2012
Fall of ground	56	65	48	40	26
Machinery	4	8	3	5	8
Transportation and mining	41	47	37	38	29
General	45	32	20	25	35
Conveyance accidents	13	2	1	3	1
Electricity	5	5	3	3	5
Fires	2	0	5	0	0
Explosives	2	4	5	4	4
Subsidence/caving	0	0	0	0	1
Heat Sickness	1	4	2	2	2
Miscellaneous	2	1	3	3	1
Total	171	168	127	123	112

systems. Furthermore, Groves *et al.* (2007) identify that the newer a person is to their job, the greater the probability is of them being involved in an accident. Especially those with less than five years experience in their present job. Thus experience in a job is a factor to keep in mind. Lastly, Hermanus (2007) states that dust and noise are inherently associated with rock breaking and in underground mines, air and light must be supplied artificially, which all have their own associated risks attached. On top of this, blasting, as well as mining itself, releases harmful gases into the underground environment. Also, often miners generally operate in cramped conditions, do heavy work and handle heavy equipment which presents ergonomic hazards. This all contributes to increased safety risks.

2.4 Influencing Factors

Grimaldi and Simonds (1989) state that the majority of incidents that fill safety records could be predicted and so cannot be considered exclusively as accidental. Furthermore, their causes and resolutions were established already by numerous similar previous occurrences. Kunar *et al.* (2010) add to this by stating that it is acknowledged that job-related hazards and individual factors influence occupational injuries. Equally important, Grimaldi and Simonds (1989) identify that performance measurement systems should identify the factors that are most substantial to achieving the desired result and should weigh them up consistently. In addition, Hofmann and Tetrick (2003) state that although most studies propose that work characteristics do affect injuries, there is little consistency concerning which work characteristics are significant (e.g. workload, job boredom, physical hazards, etc.).

According to Hoyos *et al.* (1988), all accidents derive from the three following sources, specific job oversights and omissions, general management systems and assumed risk. Specific job oversights and omissions deals with technical information systems, facilities of functional operability, maintenance and inspection as well as supervision of management. General management systems deals with plant policies, implementation of methods, staff, information flow, management services, budgets and risk assessment systems. Assumed risk deals with risks that are known but for some reason not controlled, reasons can vary from unavailability of preventive measures to unacceptable cost benefit relationships.

Hoyos *et al.* (1988) ascertain that human error is responsible for the majority of the causes of incidents and that human error is not similar for dissimilar skill levels. Wang and Guo (May 2013) confirm this by referring to Heinrich's Accident Causation Chain Theory which was developed through the exploration of 75000 accidents. From all these accidents, it was identified that 88% of them were triggered by unsafe human behaviour, 10% by the unsafe state of things and 2% were due to uncontrollable factors. In addition, Hoyos *et al.* (1988) identify some human behavioural factors that influence the occurrence of an incident. Namely, insufficient acceptance of technical safety precautions, lack of information for ability to work safely, lack of knowledge or training (limit to human capacities for perception and information processing) and production rate (pressure resulting from too little time or from compulsion to perform).

Hoyos *et al.* (1988) state that human senses are crucial to hazard identification. He lists the five human senses along with their threshold values:

- Light - A candle flame 48.3 kilometers away on a dark clear night.
- Sound - The tick of a watch under quiet conditions 6.1 meters away.
- Taste - One teaspoon of sugar in 9.1 litres of water.
- Smell - One drop of perfume diffused into the entire volume of a three room apartment.
- Touch - The wing of a bee falling on the cheek from a distance of one centimeter.

Also, Hoyos *et al.* (1988) identify that radioactivity, bacteria, viruses, electricity, too little oxygen in the air breathed and vapours emitted by solvents are a few hazards which cannot be perceived by humans.

Kunar *et al.* (2010) finds that on a daily basis, mine-workers are exposed to numerous job-related hazards such as heat, humidity, noise, dust, inadequate ventilation and slippery floors, all of which undoubtedly inflict additional pressures. Hoyos *et al.* (1988) enhance this list with identifying monotony, restrictions with respect to movement, night time and changing shifts as job-related hazards too. Furthermore, Hoyos *et al.* (1988) identify that even simple accidents tend to be complex in terms of numerous causal factors and preventive measures. Additionally, Wang and Guo (May 2013) identify four main categories that all influencing factors fall into. These are human factors (e.g. physiological, psychological, technical quality, etc.), machine factors (e.g. old or new machine, advanced level, reliability, etc.), environmental factors (e.g. temperature, humidity, illumination, noise, air quality, etc.) and management factors (e.g. scientific management, safety supervision, safety training, etc.). All four of these categories are interrelated and are explored further in the next sections.

2.4.1 Human factors

Amongst Leveson (2004), Wang and Guo (May 2013), and Wong (2010) it is agreed that between 70% to 80% of accidents are caused by human error. Wang and Guo (May 2013) add that these human factors include physiological, psychological, quality of work and safety values. Leveson (2004) defines human error as "any deviation from the performance of a specified or prescribed sequence of actions". However, as operators endeavour to become more efficient and productive and have to deal with time pressures, their instructions and written procedures are almost never followed precisely. Leveson (2004) continues that a common method for workers to apply pressure to management without actually going on strike is to work to rule, which can lead to a collapse in productivity.

Leveson (2004) identifies that humans are progressively sharing more control of systems with automation and are moving into situations of higher-level decision making with automation implementing the decisions. These changes are leading to new types of human error and a new distribution of human errors; for example, an increasingly significant factor in accidents is the inadequacies in communication between humans and machines. This lead to several recent accidents that were blamed on operator error, although they could more correctly be categorised as a consequence from flawed system and interface design. Figure 2.11 depicts the human-machine interface, the figure shows that the human has to be able to make sense of the data fed out by the machine, then make a decision about what to do and lastly manually input the action to be taken. Multiple errors can be made here, such as not fully understanding the data, not receiving enough data, forming the wrong conclusions and taking the wrong action. This leads Leveson (2004) to state that going forward from here, formulating new and more effective accident models will necessitate transferring the emphasis in explaining the role of humans in accidents from error or deviations from normative procedures to pay more attention on the mechanisms and factors that shape human behaviour.

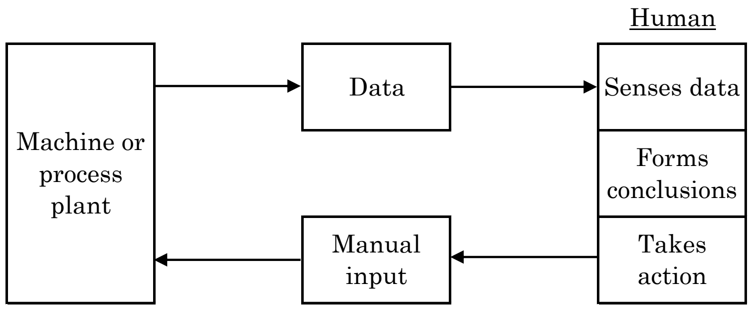


Figure 2.11: Human control loop (adapted from Wong (2010))

Wong (2010) confirms the argument of Leveson (2004) by stating that accidents are not necessarily the operators fault, often the factors that caused the operators error may be the prime cause of the accident. Furthermore, Wong (2010) defines four central factors that influence human behaviour and as such can influence an accident. These four factors are ergonomics, anthropometrics, physiology, and psychology.

Firstly, ergonomics refers to the design of machines and equipment such that it matches the capacities of the people who will be operating it. Ergonomics can be made up of the working environment (e.g. temperature, lighting, noise and space), mental capacity of humans (e.g. match the design to the mental ability and skills of the operators and maintenance staff), the human control loop (e.g. Figure 2.11), information (e.g. unambiguous and sufficient data in order to lead to a clearly defined course of action, as too much data can cause confusion and bewilderment and too little data may cause a wrong conclusion), and operator controls (e.g. the arrangement of controls must be in some logical order and in some sort of symmetry to help prevent the operator selecting the wrong item in a moment of panic or loss of concentration).

Secondly, anthropometrics deals with humans being different (e.g. different sizes and shapes due to sex or ethnicity etc.) which needs to be taken into consideration in design (e.g. short people cannot see out of a car window or an overweight person cannot work in a confined space).

Next, physiology deals with the human physical factors and limits. Wong (2010) states that despite a human having five senses, they in general only use two in the working environment, these being sight and sound. Furthermore, there are two main causes of accidents associated to physiology; these are task overload and fatigue.

Lastly, psychology is significant in how people perform as well as the attitudes they have, what is more, humans are not robots, they reason and have emotions that affect the way they behave. There are five factors that psychology can be divided into, firstly, *mental state of humans*, which are emotional factors that are challenging to account for and to detect such as lack of concentration, lack of motivation, a conscious disregard to instructions, etc. Secondly, *fixed mind set*, such as operators cutting corners because they know their performance is measured by productive output. Next, *complacency*, which refers to a relaxed state of mind without fear or stress, in this case an operator is no longer alert for possible hazardous situations. Fourthly, *mental capacity*, it is known that everyone has different capacities and overloading a person inflicts a risk of mental breakdown and possibly chronic depression. Lastly, *communication* should be clear, for example, management needs to ensure a suitable shift overlap to allow clear communication between shifts to prevent anything being misunderstood.

Hoyos *et al.* (1988) identify factors that influence human errors, these factors are very similar to those identified by Wong (2010) stated above. Hoyos *et al.* (1988) influential factors are presented below:

- Causes of human malfunctioning
  - External events
  - Excessive task demands
  - Operator capacity
  - Human variability
- Situational factors
  - Task characteristics
  - Physical environment
  - Work time characteristics
- Performance shaping factors
  - Subjective goals
  - Mental load
  - Affective components
  - Physiological stressors

Paul and Maiti (2005) identify that employees who are more involved in their jobs exhibit better safety performance, which consequently diminishes occupational injuries. Furthermore, occupational stress and the safety environment predict the employee's job involvement and occupational hazards induce more occupational stress in the workers while social support mitigates the same. This leads Paul and Maiti (2005) to conclude that job stress and the safety environment are the two key factors that influence work related injuries in mines. Furthermore, Kunar *et al.* (2010) and O'Toole (2002) identify age to influence the occurrence of accidents; they believe that younger people are more likely to suffer occupational injury due to a lack of knowledge.

In addition to this, Hoyos *et al.* (1988) identify more human behavioural factors that influence the occurrence of incidents. Namely, insufficient acceptance of technical safety precautions, lack of information in order to work safely, lack of knowledge or training (limit to human capacities for perception and information processing), and production rate (pressure resulting from too little time or from compulsion to perform).

Hoyos *et al.* (1988) identify repetitive work as a factor that influences accidents, additionally, repetitive work can lead to fatigue and as Wong (2010) says, fatigue is a major cause of accidents. Furthermore, Theron and van Heerden (2011) identify that fatigue is one of the major causal and/or contributing factors when it comes to causes of fatalities in the mining industry. Additionally, Schutte (2010) confirms this by stating that there have been numerous accidents in the South African mining industry where fatigue was acknowledged as either causal or contributory.

Schutte (2010) and Theron and van Heerden (2011) identify that fatigue is not merely tiredness, but also a feeling of weariness or a deficiency of energy that does not go away with rest, and it has a direct effect on alertness and work performance. Theron and van Heerden (2011) identify two varieties of fatigue, namely, physical fatigue in which a person's muscles are unable to perform activities as effortlessly as they normally do, and psychological fatigue in which it is a challenge to concentrate for extended periods of time.

Theron and van Heerden (2011) identifies the harshness of fatigue by stating that by remaining awake for 17 hours is equivalent to having a 0.05 blood alcohol level, and by staying awake for 20 hours is equivalent to having a 0.1 blood alcohol level. Currently in South Africa, the legal blood alcohol limit to drive is 0.05 and to enter some mines this limit is 0.00. However, fatigue cannot be picked up through a simple breathalyser and as such, organisations need to be very cautious of fatigue.

Schutte (2010) identifies that high levels of fatigue cause reduced performance and productivity in the workplace and increase the threat of accidents and injuries taking place, as well as affecting the capacity to think clearly, which is imperative when making safety related decisions and judgements. Theron and van Heerden (2011) add to this by stating that a person's capacity to function can be significantly affected by fatigue. This leads to the understanding that the effects of fatigue include decreased performance and productivity and increased potential for incidents/injuries to transpire. Fatigue can lead to incidents/injuries due to it affecting a number of key mental and physical abilities. For example, fatigue can result in impaired concentration, poor judgement, reduced hand-eye coordination and slower reaction times.

Lastly, Schutte (2010) identifies that the threat of fatigue is inherent in shift work and work that is physically or mentally demanding, repetitive or requiring high vigilance. Theron and van Heerden (2011) add that fatigue can be a normal and important human response to physical exertion, poor eating habits, emotional stress, boredom or lack of sleep and thus needs to be handled and controlled cautiously.

2.4.2 Machine factors

According to Wang and Guo (May 2013), there are three important machine factors that influence accidents which include equipment condition, ability to adapt to the change of the external environment and machine running stability. It should also be noted that, an item of equipment failing and triggering an incident is not necessarily the root cause of the incident but improper or insufficient maintenance, which linked to human behaviour, could be identified as the root cause of the incident and not the equipment. However, with respect to this research and for the purpose of this study, these factors will not be included due to the fact that the model to be created is focussed on being mine specific and not equipment specific. Although, it should be stated that the occupation section under the management factors will account for factors such as if the employee works behind a desk or is involved in hauling etc., because occupation is a more generalised and measurable factor linking groups of equipment to employees that work with them.

2.4.3 Environmental factors

As identified by Wang and Guo (May 2013), the environmental factors that influence accidents include, temperature, humidity, lighting, noise, dust, toxic and harmful concentrations of gases in the underground working environment. For the purpose of this section, three groupings have been used, namely, time of day, temperature & humidity and noise. The lighting factor will be combined into the time of day. The location factor, dust and toxic and harmful gases will be incorporated into the occupation factors, under the management factors.

2.4.3.1 Time of day

Temperature, humidity, and lighting are a few of the environmental factors influencing incidents as identified by Wang and Guo (May 2013) and Wong (2010). These three factors can be loosely related to the time of the day, as well as the time of year, thus the section on time of day relating to incidents is explored.

Hoyos *et al.* (1988), Theron and van Heerden (2011), and Schutte (2010) all agree that more accidents occur during night shifts because it is more demanding to concentrate at night when a person would ordinarily be sleeping/resting. Additionally, the physiological inclination to sleep at night and to be awake during the day is influential, and problems can occur when disrupting this tendency. This can lead to fatigue, as discussed earlier, which causes reduced workplace performance and productivity, as well as an increased risk of accidents and injuries.

However, in research performed by Jansen and Brent (2005) amongst multiple mines in Rustenburg in 2003, the majority of fatal accidents occurred during the morning shift when early inspection takes place and working areas are being made safe. Additionally, 33% of the fatally injured were in supervisory positions, indicating possible inadequate safety awareness.

Furthermore, Attwood *et al.* (2006) identify from a statistical analysis of a database of more than one thousand offshore accidents, in an attempt to extract possible relationships between the accidents and the operations being undertaken at the time, that about 32% of injuries between 10am and 11am were categorised as fatal or major, compared to 19% for the remaining 23 hours. Figures 2.12 and 2.13 represent the actual accidents and fatalities by time of day in 2010 as presented by the South African Department of Mineral Resources (DMR). From these figures it can be seen that fatal and non-fatal injuries are more prominent during the working day (7am to 4pm), which is counterintuitive with regards to the earlier discussion.

However, one can deduce that despite it being seen as more dangerous to work late at night, there are more employees working during the day and thus the sample space exposed to hazards and risks during the day time is larger and hence more accidents occur during the day. Another possible explanation for these graphs could be that maintenance of equipment generally only occurs during the day shift and there is a high risk for injury during maintenance.

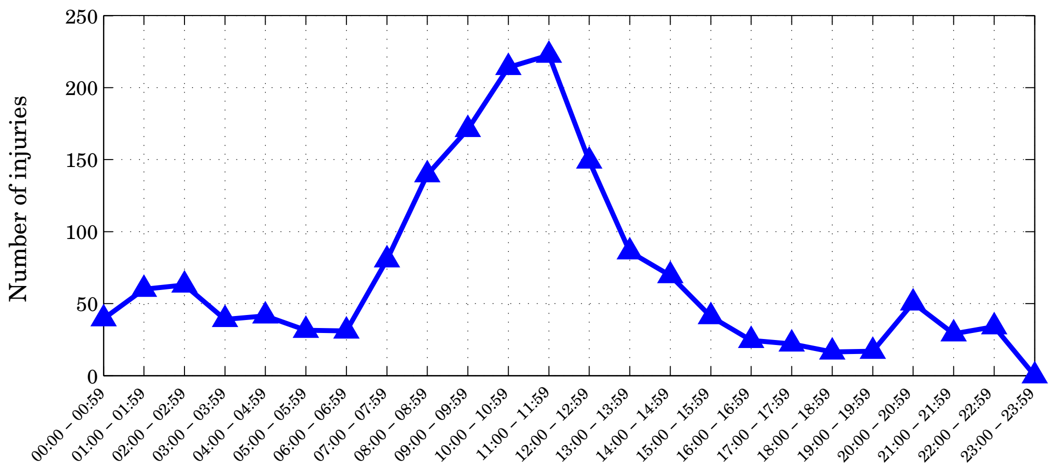


Figure 2.12: Actual injuries by time of day 2010 (adapted from South African Department of Mineral Resources (2013*b*))

2.4.3.2 Temperature & Humidity

As identified by Wang and Guo (May 2013), Wong (2010) and Kunar *et al.* (2010), temperature and humidity are two work related hazards miners are exposed to daily, which undoubtedly impose additional stresses and partake in influencing the occurrence of an accident. Theron and van Heerden (2011) add that workers exposed to thermal stress for prolonged periods become fatigued which leads to heat exhaustion and contributes to multiple physiological disturbances such as excessive cardiovascular strain and hyperthermia. Also, as discussed earlier, fatigue is a prominent contributing factor to accidents.

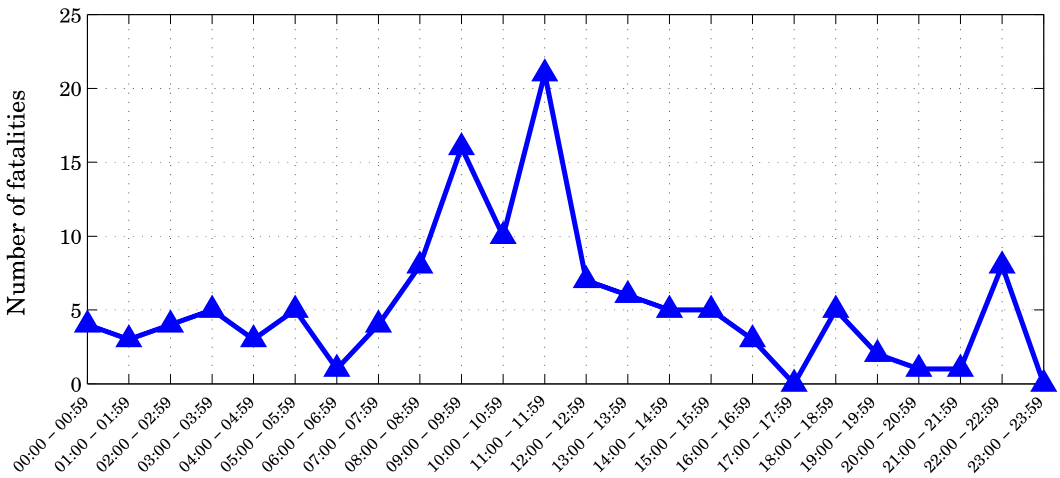


Figure 2.13: Actual fatalities by time of day 2010 (adapted from South African Department of Mineral Resources (2013*a*))

Hoyos *et al.* (1988) identify that in a work environment of temperatures over 30°C, there is an evident and relatively radical deterioration in performance which increases unsafe worker behaviour and thus increases the potential for an accident to occur.

HSE (2014) and National Weather Service (2014) define the Wet Bulb Globe Temperature (WBGT) as the most widely used and accepted index for the assessment of heat stress in industry. It is a measure of the heat stress which takes into account temperature, humidity, wind speed, sun angle and cloud cover (solar radiation). Additionally, Ramsey *et al.* (1983) state that the WBGT is the recommended thermal index by the National Institute for Occupational Safety and Health. Donoghue *et al.* (2000) recognise that in South African underground Gold mines, a WBGT of 26.5°C to 28.3°C and higher can cause heat stroke.

In Figure 2.14 the Unsafe Behaviour Index (UBI) is plotted as a function of WBGT. This is a predicted second order regression for three different workloads (light, medium, and heavy) as presented by Ramsey *et al.* (1983). From the study of Ramsey *et al.* (1983), it was established that the region of preferred WBGT temperature was 17°C to 23°C. This is an optimal range of thermal conditions within which people demonstrate the best performance in terms of error rates, learning time and production values. Outside of this range an individual's performance deteriorates.

Donoghue *et al.* (2000) deliberate the reasoning for the incidence of heat exhaustion increasing during summer and at depth underground. This is due to increased temperature and humidity in deep underground mines. Furthermore, Donoghue *et al.* (2000) identify six factors that affect this increase in temperature, firstly, the surface air temperature and humidity may be high to begin with. Secondly, rock temperature increases with depth, this is known as geothermal gradient. Thirdly, air temperature also increases with depth due

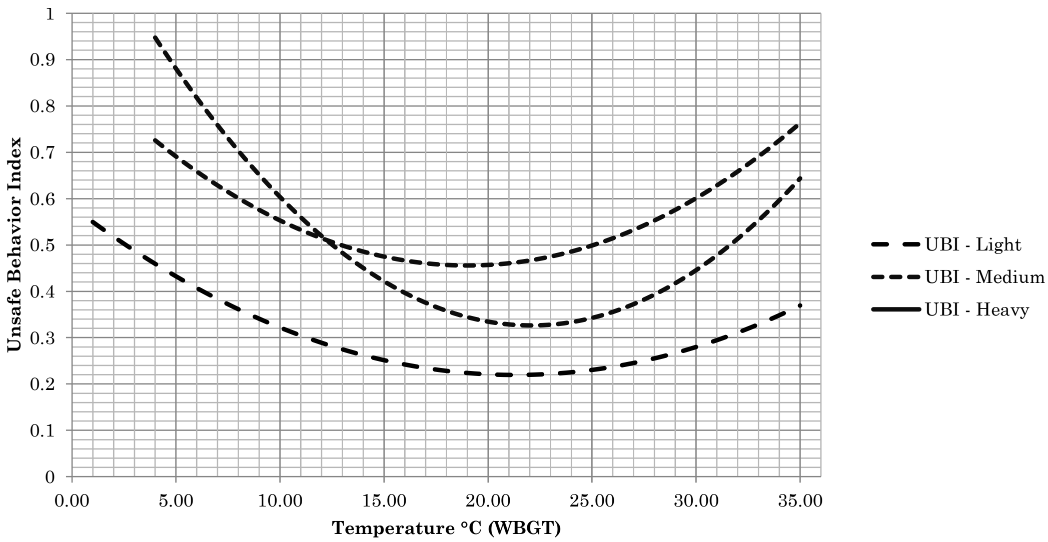


Figure 2.14: UBI versus temperature recreated from Ramsey *et al.* (1983)

to increasing air pressure, this is known as auto-compression. Next, groundwater and mine water transfer heat to the air by evaporation and increase the humidity. Also, most of the energy consumed by mining machinery and equipment is liberated as heat, be it electrical, compressed air, or diesel. Lastly, less important sources of heat underground include human metabolism, oxidation processes, explosives blasting, rock movement and pipelines.

2.4.3.3 Noise

Wilkins and Acton (1982), Wong (2010), Wang and Guo (May 2013), and Theron and van Heerden (2011) all agree that noise is a factor that leads to accidents as well as increased fatigue. It reduces alertness, overpowers acoustic signals such as warning cries, sirens and machine sounds and it hinders communication when protective devices must be worn to protect ones hearing (e.g. PPE). Furthermore, Hoyos *et al.* (1988) identify a relationship between the average number of errors and increasing noise in tasks demanding optical vigilance. In addition, Kunar *et al.* (2010) and Hermanus (2007) identify that noise levels are known to be high in mines and as such miners are exposed daily to noise which will impose additional stresses.

Hermanus (2007) continues that the well-known problem in mining, noise exposure, is due to the use of heavy equipment, drilling and rock breaking, transferring material, sorting and milling of rock, and confined working conditions. Hermanus (2007) identifies that from available data for noise exposure to South African miners, that nearly half the employees are exposed to deafening noise, and of these workers, more than 90% work in zones in which noise exceeds the 85dBA time weighted average, with 11% working in zones in which the noise levels are even higher.

2.4.4 Management factors

As identified by Wang and Guo (May 2013), management factors include, co-ordination of people, machine and environmental factors in production, no loopholes in management, and no defects in a system. This section focuses on three factors, namely, production rate which relates to the stress placed on an employee, shift length which incorporates the time into the shift, and occupation which acknowledges there are different risks associated with different occupational functions in the mining sector. The effects of management interventions are not explored.

2.4.4.1 Production rate

Wong (2010), Wang and Guo (May 2013), and Hoyos *et al.* (1988) identify that overloaded production, production rate and task overload are some main causes of accidents. Production rate influences the occurrence of accidents because it generates a pressure resulting from insufficient time to complete a task or it creates a compulsion to perform, at which time safety is not a primary concern. Additionally, Ramsey *et al.* (1983) identify that higher workloads, result in higher values of UBI. Paul and Maiti (2005) add to this by identifying that production pressure is a significant factor in accident development. Furthermore, Paul and Maiti (2005) state that pressure on production seems to lead to an escalation in disabling injuries, which as a consequence reduces the production. Lastly, Leveson (2004) finds that written procedures and instructions are seldom followed precisely as workers endeavour to become more efficient and productive and have to deal with time pressures. This also leads to the increased potential for accidents to occur.

2.4.4.2 Shift length

Ramsey *et al.* (1983) identify that the time into the shift has noteworthy effects on worker safety related behaviour. Furthermore, Attwood *et al.* (2006) identify that in the off shore oil and gas industry, in the first hour subsequent to a shift change a large percentage of accidents occurred. Moreover, Hoyos *et al.* (1988) identify that the risk of an accident is higher during a shift change. Lastly, Theron and van Heerden (2011) identify that irregular working hours can cause fatigue which in turn influences the occurrence of incidents.

2.4.4.3 Occupation

Maiti and Bhattacherjee (2001), O'Toole (2002) and Wang and Guo (May 2013) identify that workplace location influences the occurrence of accidents. Karra (2005) states that with respect to location in the mining sector, occupational risk in underground mining is much higher than in surface mining. Furthermore, the location can in general be linked to the occupation, for example, mechanics work in certain locations primarily, and drillers work in different locations primarily. Thus the occupation is explored as an influential factor.

Karra (2005), Paul and Maiti (2005), O'Toole (2002), and Maiti and Bhattacherjee (2001) identify that occupation groups or job categories are predictor variables that influence the occurrence of accidents. Paul and Maiti (2005) state that haulage workers are the most accident prone work group, followed by loaders, due to slip and fall being a major contributory cause of the accident occurrences. Kunar *et al.* (2010) add that material handling related hazards are more influential factors for injuries compared to other job hazards in underground coal mines.

2.5 Modelling Techniques

According to ScienceDaily (2014) a mathematical model is an abstract model that uses mathematical language to describe the behaviour of a system. In addition to this, de Vries (2001) identifies mathematical modelling as the use of mathematics to describe and explain real-world phenomena, investigate important questions about the observed world, test ideas and make predictions about the real world, as can be seen in Figure 2.15. Klir and Yuan (1995) add that the purpose of constructing models is to understand some phenomenon of reality, be it natural or man-made, to make adequate predictions or retrodictions, to learn how to control the phenomenon in any desirable way and how to utilise all these capabilities for various ends. Furthermore, de Vries (2001) states that there is no best model, only better models. He quotes Howard Emmons about the challenge in mathematical modelling,

> "The challenge in mathematical modelling is not to produce the most comprehensive descriptive model but to produce the simplest possible model that incorporates the major features of the phenomenon of interest."

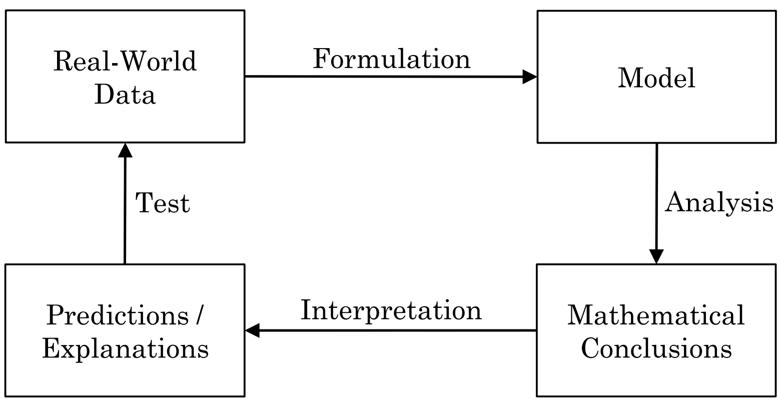


Figure 2.15: The process of mathematical modelling (adapted from de Vries (2001))

Lastly, Klir and Yuan (1995) identify that the aim in model construction is to attempt to always maximise its utility. This is connected closely with the relationship amongst three key characteristics of every systems model: uncertainty, complexity and credibility. Uncertainty can be very valuable when considered in connection to the other characteristics of systems models. In general, allowing more uncertainty tends to reduce complexity and increase credibility of the resulting model. The challenge is to find an optimum level of uncertainty for the problem at hand. This section on modelling techniques covers five techniques, namely, Artificial Neural Networks (ANN), Fuzzy Logic, Support Vector Machine (SVM), Hidden Markov Model (HMM), and Learning Decision Trees.

2.5.1 Artificial Neural Networks (ANN)

Page *et al.* (1993) and Nelles (2001) state that Artificial Neural Networks (ANN) materialised from studies of biological structures of how human and animal brains perform operations, which are tremendously powerful for tasks such as information processing, learning and adaption. Russel and Norvig (2010) add that ANN have the aptitude to execute distributed computation, withstand noisy inputs and learn, however, regardless of Bayesian networks having the same properties, ANN persist as one of the most prevalent and effective forms of learning systems. Page *et al.* (1993) suggest that ANN are popular due to their capacity to characterise non-linear systems. Furthermore, Page *et al.* (1993) and Nelles (2001) identify four central attributes of neural networks as described below,

- Capability of learning by example.
- The trained network is capable of producing sensible outputs when presented with new unseen input data.
- Robust to noisy data that occurs in real world applications.
- In general, network performance does not significantly degenerate if some of the network connections become faulty.

Larose (2005) confirms that with respect to noisy data ANN are robust because the network comprises of multiple nodes, with every connection assigned different weights, thus an ANN can acquire the ability to function around uninformative examples in a data set. Mitchell (1997) adds that ANN can be used for decision tree learning tasks with comparable accuracy. Furthermore, Mitchell (1997) identifies that ANN are one of the most effective learning methods for learning to understand multifaceted everyday data, as well as they offer a general, practical method for learning real-valued, discrete-valued and vector-valued functions from examples.

Nelles (2001) and Page *et al.* (1993) find that the most broadly recognised and used ANN architecture is the Multilayer Perceptron (MLP) network. The MLP network is comprised of one input layer, multiple hidden layers (usually one or two) and one output layer, as can be seen in Figure 2.16. Page *et al.* (1993) add that the MLP network can accurately characterise any continuous non-linear function connecting the inputs to outputs. Furthermore, Russel and Norvig (2010) state that with one adequately sized hidden layer, representing any continuous function of the inputs with good accuracy is possible, and with two hidden layers even discontinuous functions can be represented. However, Russel and Norvig (2010) find that very large networks generalise well if the weights are kept small, otherwise the large networks may memorise all the training examples and then not generalise well to new unseen inputs, which is known as over-fitting.

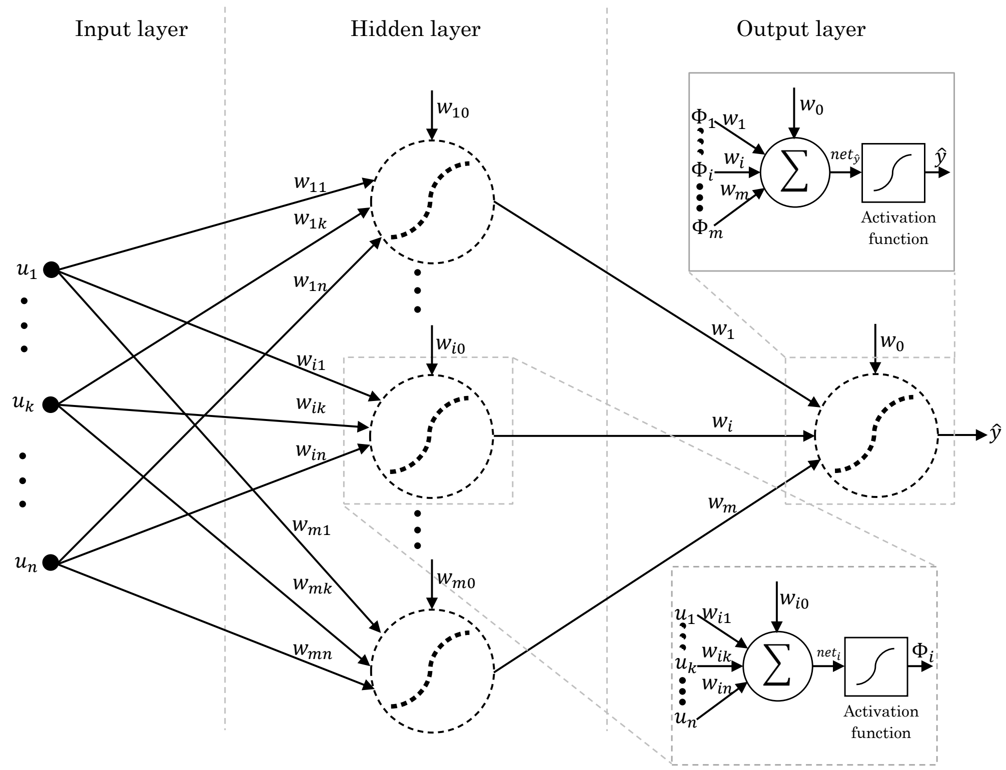


Figure 2.16: Schematic of a MLP Artificial Neural Networks (ANN) model with one hidden layer (adapted from Nelles (2001))

Page *et al.* (1993) state that in a MLP network the outputs of each node in a layer is linked to the inputs of all the nodes in the subsequent layer. For one hidden layer as in Figure 2.16, the output neuron, $\hat{y}$, is a linear combination of the hidden layer neurons, Φ_i, with an offset (or bias or threshold), w_0, which is expressed mathematically in Equation 2.5.1.

$$\hat{y} = \sum_{i=0}^{m} w_i \Phi_i (\sum_{j=0}^{n} w_{ij} u_j) \tag{2.5.1}$$

where:

m is the number of hidden neurons.

n is the number of inputs.

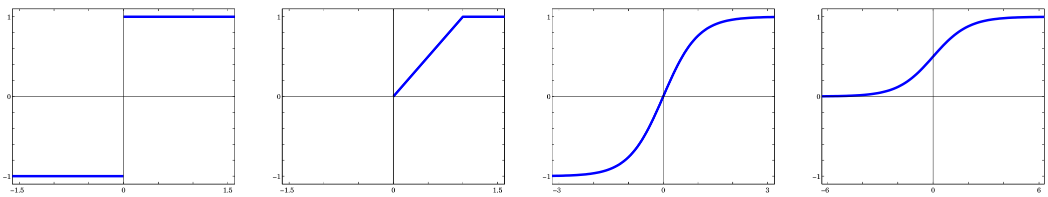
w_i are the output layer weights.

w_{ij} are the hidden layer weights.

u_j are the inputs.

Φ_i is the output from the hidden layer neurons.

An activation function is a function which defines the output of a node. It scales the output value to a discrete value of '0' or '1' (Hard Limiter), or to a continuous value between '0' and '1' (Sigmoid, Threshold) or '-1' and '1' (Tanh), depending on the function selected. Four activation functions are identified from the text, and they are presented in Figure 2.17. Of these activation functions, Page *et al.* (1993), Russel and Norvig (2010), Nelles (2001), Mitchell (1997), and Larose (2005) all agree that the sigmoid (or logistic) function is the most common activation function used. Furthermore, Russel and Norvig (2010) state that the sigmoid function is most popular, because it is differentiable.



(a) Hard limiter (b) Threshold (c) Tanh (d) Sigmoid

Figure 2.17: Activation functions (adapted from Page *et al.* (1993) and Nelles (2001))

Page *et al.* (1993) state that training the model using a set of input and output data determines the suitable values for the network weights (including the bias). Furthermore, Page *et al.* (1993) state that training speed is influenced by the quantity of nodes in the network and therefore the quantity of nodes necessary should be determined by the complexity of the relationships between the input and output data. They suggest using a Principal Component Analysis (PCA) as a technique to measure the relative contribution of the inputs to output variations. Additionally, they propose using the PCA values to initialise the weights for the model, although Mitchell (1997) recommends initialising all the network weights with small random values between -0.5 and 0.5. Notwithstanding which method is used to initialise the weights, numerous texts suggest that the back-propagation algorithm is used for training the model, as it is the most popular technique. Mitchell (1997) adds that multilayer networks trained with back-propagation are capable of expressing a large variety of non-linear decision surfaces.

Mitchell (1997) states that the back-propagation algorithm for a multilayer network learns the weights using a gradient descent optimisation to try minimise the squared error between the network output values and the target values for these outputs. Equation 2.5.2 presents the mathematical representation for the squared error between the network output values and the target values for these outputs.

$$E(\vec{\mathbf{w}}) \equiv \frac{1}{2}\sum_{d\in D}\sum_{k\in O}(t_{kd} - o_{kd})^2 \tag{2.5.2}$$

where:

d is the training example.

D is the set of training examples.

k is the k^{th} output.

O is the set of output units in the network.

t_{kd} is the target value of the k^{th} output and d^{th} training example.

o_{kd} is the output value of the k^{th} output and d^{th} training example.

Mitchell (1997) continues, that in multilayer networks multiple local minima can be found on the error surface and the gradient descent search is only guaranteed to converge towards some local minima and not necessarily the global minimum error. However, despite this, back-propagation still produces outstanding results. The back-propagation algorithm starts by creating a network with the preferred number of hidden and output nodes and all weights are initialised. Then for each training example, it applies the network to the example, computes the gradient with respect to the error on this example, then updates the weights in the network. This gradient descent step is then iterated until the network performs acceptably well.

2.5.2 Fuzzy logic

Ross (2010) identifies that for a typical problem, just a minor portion of knowledge or information might be considered as certain or deterministic, and Klir and Yuan (1995) confirm this by stating that uncertainty is unavoidable. Additionally, Nguyen and Walker (2005) state that conveying knowledge and information using every day natural language has a copious amount of imprecision and vagueness, or fuzziness. For example, statements such as, "Jaco is short" and "Marinel is young" are vague. A primary concern from such imprecise statements is how to represent, manipulate and draw inferences from them. Moreover, Klir and Yuan (1995) identify that linguistic concepts are vague as well as context dependent, for example, a large distance has different meanings in the context of walking, driving or air travel.

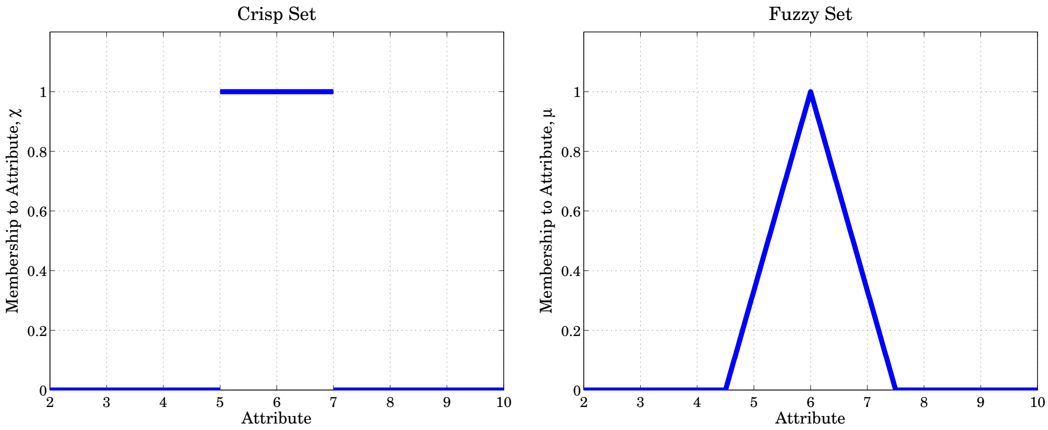
Ross (2010) finds that the larger the uncertainty in a problem, the less precise the understanding of that problem will be and over time, this uncertainty has been named fuzziness. As stated by Nelles (2001), fuzzy logic was invented in 1965 by Zadeh as an extension of Boolean logic. Ross (2010) continues that when considering the use of fuzzy logic for any given problem, the need for exploiting the tolerance for imprecision should be considered. Klir and Yuan (1995) add that fuzzy sets offer a meaningful and powerful representation of measurement uncertainties, as well as meaningful representation of vague concepts expressed in natural language. Furthermore, Ross (2010) identifies that fuzzy sets provide a mathematical approach to characterise vagueness and fuzziness in humanistic systems.

Ross (2010) identifies that algebraic functions map an input variable to an output variable, and that fuzzy systems map an input group to an output group, of which these groups can be linguistic propositions or other forms of fuzzy information. A major advantage of fuzzy systems theory is to approximate system behaviour where analytical functions or numerical relations do not exist. Klir and Yuan (1995) add that fuzzy sets are sets with boundaries that are not precise and that the membership in a fuzzy set is a matter of a degree, rather than a matter of affirmation or denial. Lastly, Ross (2010) identifies that fuzzy systems are primarily used in deductive reasoning, which is the kind of thinking were specifics are inferred from the general.

Ross (2010), Klir and Yuan (1995), and Nelles (2001) distinguish the difference between crisp sets and fuzzy sets. They identify that crisp sets are precise and assign a value of 1 for *true* and 0 for *false*, thus they have no grey areas (for example, identifying the set of heights from 5 to 7 feet). However, fuzzy sets are imprecise and assign a value on the interval $[0, 1]$ dependant on the degree of membership to the attribute tested (for example, the set of heights in the region around 6 feet). Figure 2.18 represents these examples, and as can be seen in the figure, a height of 6 feet would receive a value of 1/*true* or 100% membership for a crisp and fuzzy set respectively, however, a value of 4.999 feet is not far off from 6 feet yet as a crisp set it would have a value of 0/*false*, although as a fuzzy set it will have a small degree of membership to the attribute of *around* 6 *feet*.

Klir and Yuan (1995) identify that crisp sets are unrealistic due to unavoidable measurement errors, despite them being mathematically correct. Furthermore, fuzzy variables are more adjusted to reality since they capture measurement uncertainties as a part of the experimental data. Additionally, data based on fuzzy variables provides more accurate evidence about real phenomena than data based upon crisp variables.

Ross (2010) states that in crisp sets, the transition is abrupt and well defined for an element in the universe between membership and non-membership in a given set. Whereas for an element in the universe that contains fuzzy sets, this transition can be gradual due to the vague and ambiguous boundaries. Klir and Yuan (1995) add that a fuzzy set can be defined mathematically by



(a) Crisp set for heights from 5 to 7 feet (b) Fuzzy set of heights around 6 feet

Figure 2.18: Comparison of crisp sets and fuzzy sets (adapted from Ross (2010))

assigning individuals a value representing its grade of membership in the fuzzy set. This grade corresponds to the degree to which that individual is similar or compatible with the concept represented by the fuzzy set. For example, in Figure 2.19, if the temperature is 2.5°C, that corresponds to a low temperature to the degree of 0.75, and a medium temperature to the degree of 0.25.

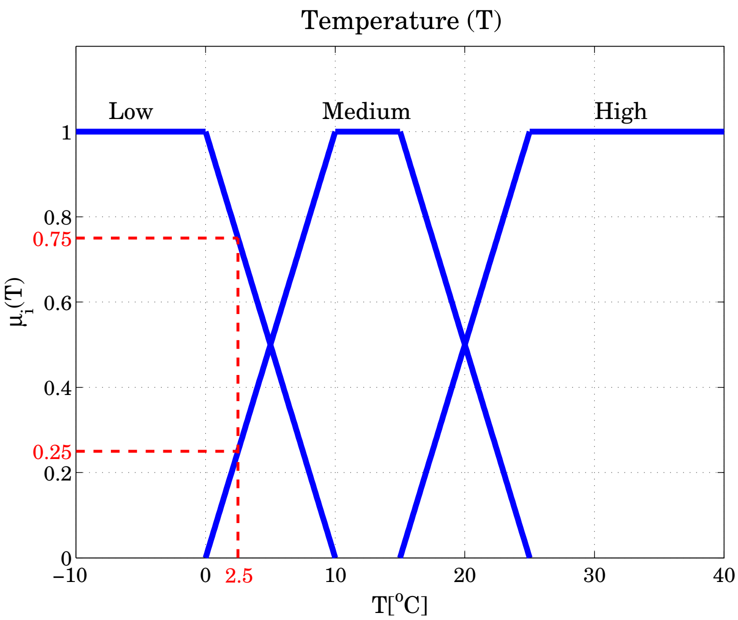
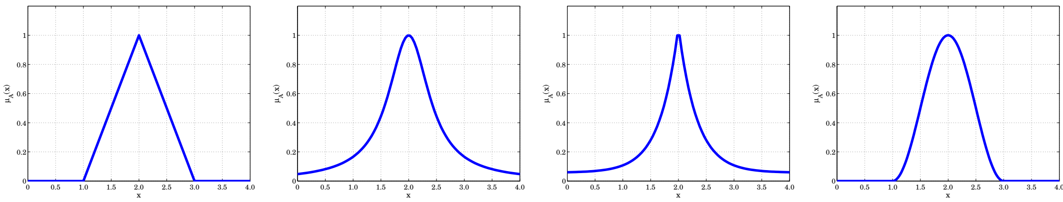


Figure 2.19: Fuzzy membership functions for low, medium, and high temperature (adapted from Nelles (2001))

Nelles (2001) states that the trapezoidal and triangular membership functions, such as in Figure 2.18 and Figure 2.19, lead to information losses where the slope is equal to zero. Furthermore, these types of membership functions are not differentiable and thus learning from data may have problems. Nelles (2001) identifies normalised Gaussians to be used as membership functions instead. However, Klir and Yuan (1995) offer more alternatives for membership functions as can be seen in Figure 2.20, although, Klir and Yuan (1995) state that many applications are not overly sensitive to variations in the shape and thus it is convenient to use a simple shape such as a triangle or trapezoid.



(a) Triangular (b) $\frac{1}{1+p(x-r)^2}$ (c) $e^{-|p(x-r)|}$ (d) Cosine

Figure 2.20: Possible shapes of membership functions for fuzzy sets (adapted from Klir and Yuan (1995))

Lastly, defuzzification is the process of reducing a fuzzy set to a crisp single-valued quantity, where fuzzification is merely the converse. There are multiple methods for defuzzification (e.g. maximum membership principle, centroid method, weighted average method, etc.), all of which are capable of identifying a precise quantity from a fuzzy set.

2.5.3 Support Vector Machine (SVM)

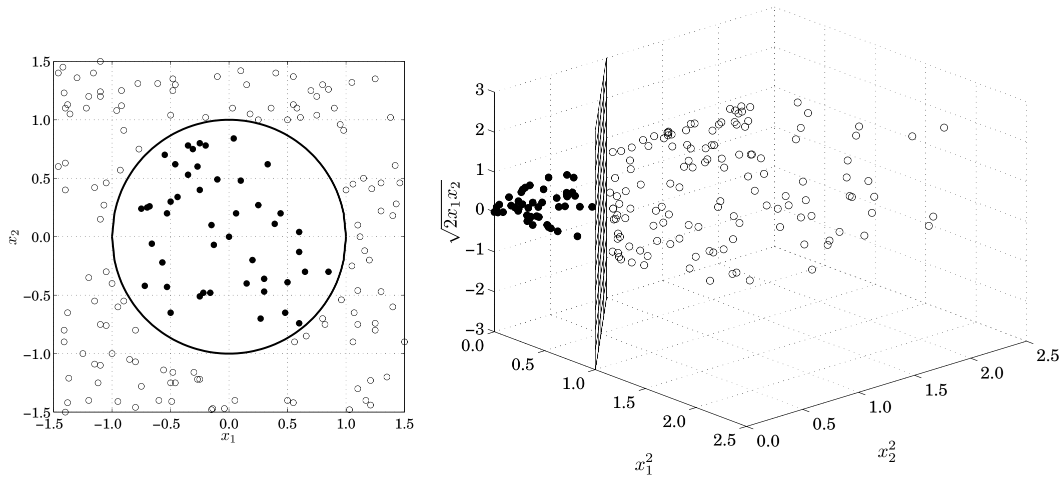
Murty and Devi (2011) identify that Support Vector Machine (SVM) is a binary classifier which extracts a decision boundary in multi-dimensional space using an appropriate sub-set of the training set of vectors; the elements of this sub-set are known as the support vectors. Geometrically, support vectors are those training patterns that are closest to the decision boundary. Steinwart and Christmann (2008) adds that the number of support vectors has a direct impact on the time required to evaluate the SVM decision function, as well as the time required to train the SVM. Hamel (2009) states that linear classifiers based on SVMs can easily extend to non-linear classifiers and that kernel functions are at the core of this generalisation. Interestingly, non-linear SVMs preserve the efficiency of finding linear decision surfaces but allow the application of these classifiers to training sets that are not linearly separable.

Hamel (2009) identifies that SVM can be generalised by allowing the underlying maximum-margin classifier to make mistakes on the training set. This is accomplished through the introduction of slack variables. Although this is counterintuitive, real-world training sets are not faultless and do contain noise. Simple decision surfaces tend to generalise better and therefore have a higher probability of classifying points correctly that are not part of the training set.

Cristianini and Shawe-Taylor (2000) state that SVM is a learning system that uses hypothesis space of linear functions in a high dimensional feature space, trained with a learning algorithm from optimisation theory that implements a learning bias derived from statistical learning theory. Furthermore, the four problems of efficiency of training, efficiency of testing, over-fitting and algorithm parameter tuning are all avoided in the SVM design.

Russel and Norvig (2010) state that the core of SVM is that some examples are more significant than others, and that paying attention to them can lead to better generalisation. Furthermore, some examples can appear close to the problem decision boundary such that a minor disturbance would shift it outside the decision boundary. SVM beats this by attempting to minimise expected generalisation loss rather than minimising expected empirical loss. Although it is unknown where new points may fall, under the probabilistic assumption, it can be assumed that they will come from the same distribution as the previously seen examples.

As can be seen in Figure 2.21, if examples are not linearly separable, then the inputs can be mapped to new vectors $\Phi(x)$. If data is mapped into a space of sufficiently high dimensions, then they will almost always be linearly separable. The resulting linear separators when mapped back to the original input space, can correspond to arbitrarily wiggly, non-linear decision boundaries between the positive and negative examples. Schölkopf and Smola (2002) adds that by mapping the input data non-linearly (via Φ) into a higher-dimensional feature space (e.g. $\mathbb{R}^2 \rightarrow \mathbb{R}^3$) and constructing a separating hyper plane there, an SVM corresponds to a non-linear decision surface in the input space.



(a) $\mathbb{R}^2$ (b) $\mathbb{R}^3$

Figure 2.21: Schematic of SVM mapping (adapted from Russel and Norvig (2010))

Schölkopf and Smola (2002) depict the SVM architecture as can be seen in

Figure 2.22. Schölkopf and Smola (2002) continue, that if the kernel function k is chosen first, it determines the type of classifier (e.g. polynomial classifier, radial basis function classifier or neural network). All the other parameters (number of hidden units, weights, threshold b) are found during training, by solving a quadratic programming problem. The first layer weights x_i are a subset of the training set (the support vectors), the second layer weights $\lambda_i = y_i\alpha_i$ are computed from the Lagrange multipliers. The classification equation is presented in Equation 2.5.3.

$$f(x) = sgn(\sum_i \lambda_i k(x, x_i) + b) \tag{2.5.3}$$

where:

λ_i is the weight.

$k(x, x_i)$ is the kernel function.

b is the threshold.

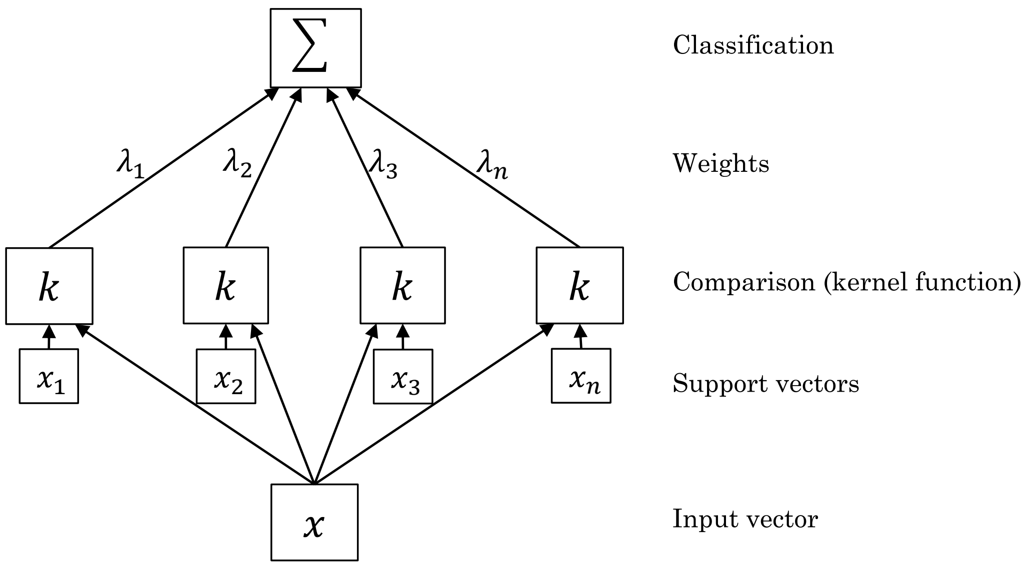


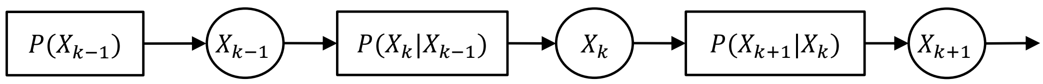
Figure 2.22: Schematic of SVM architecture (adapted from Schölkopf and Smola (2002))

2.5.4 Hidden Markov Model (HMM)

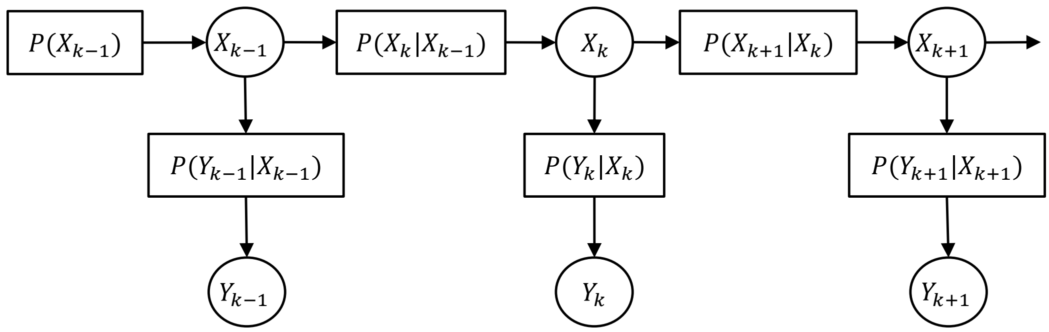
As stated by Cappé *et al.* (2005), a Hidden Markov Model (HMM) is a discrete time process $\{X_k, Y_k\}_{k\geq 0}$, where $\{X_k\}$ is a Markov chain and, conditional on $\{X_k\}$, $\{Y_k\}$ is a sequence of independent random variables such that the conditional distribution of Y_k only depends on X_k. However, Zucchini and

MacDonald (2009) identify that the basic HMM is based on a homogeneous Markov chain and has neither trend nor seasonal variation. Furthermore, the observations can be either discrete valued or continuous valued. Cappé *et al.* (2005) continue by stating that the Markov chain $\{X_k\}_{k\geq 0}$ is hidden and thus not visible, however what is visible is an alternative stochastic process $\{Y_k\}_{k\geq 0}$, connected to the Markov chain in that X_k governs the distribution of its corresponding Y_k. Zucchini and MacDonald (2009) add that the distribution of Y_k depends exclusively on the current state of X_k and not on the previous states or observations.

Murty and Devi (2011) add to this discussion, that state transitions are probabilistic and observations are probabilistic functions of state which deals with noise in the data, and consequentially, the classifier evades over-fitting and generalises well. Furthermore, Zucchini and MacDonald (2009) identify that HMMs allow the probability distribution of each observation to depend on the unobserved state of a Markov chain, which accommodates over-dispersion and serial dependence. Lastly, Cappé *et al.* (2005) find that the hidden states make the model generic enough to deal with a multitude of multifaceted real-world time series, while the reasonably simple prior dependence structure still allows for the use of efficient computational procedures. Figure 2.23 presents a schematic of how a simple Markov model and a simple HMM look.



(a) Markov Model



(b) Hidden Markov Model

Figure 2.23: Markov Model and Hidden Markov Model factor graphs (adapted from Koski and Noble (2009))

Fraser (2008) states two assumptions of a HMM, firstly, the observations are conditionally independent of the states (e.g. given the current state, the probability of the current observation is independent of states and observations at all earlier times).

$$P_{Y(k)|X_1^k,Y_1^{k-1}} = P_{Y(k)|X(k)} \tag{2.5.4}$$

Then secondly, the state process is Markov (e.g. given the current state, the probability of the next state is independent of earlier states. Combined with the first assumption, this implies that the next state is also conditionally independent of past observations).

$$P_{X(k+1)|X_1^k,Y_1^k} = P_{X(k+1)|X(k)} \tag{2.5.5}$$

For example, a day can be classified as sunny (S), rainy (R), or cloudy (C). A typical week in summer would be '$SSSSSSS$', and in winter '$RRRRRRR$'. This is in the ideal world, however, in summer some days could be rainy or cloudy. Furthermore, transition from one day to the next is probabilistic.

$S \to S$ is more likely during summer.

$S \to R$ is more likely during the rainy season.

Classes of patterns can be characterised using a HMM, where each pattern is regarded as a sequence of states. Perchance the actual state can be hidden and merely its probabilistic variations are visible. For example, if we are sealed in an apartment and cannot see outside if it is sunny, cloudy, or rainy, we could discern whether a guest has an umbrella or not, as well as pick up the sound of rain.

2.5.5 Learning decision trees

Mitchell (1997) identifies decision tree learning as one of the most practical and extensively used methods for inductive inference. He states that it is a technique for approximating discrete-valued functions that is robust to noisy data and capable of learning disjunctive expressions. Russel and Norvig (2010) add to this by stating that decision tree induction is one of the simplest and most successful forms of machine learning. They continue that a decision tree represents a function that takes an input as a vector of attribute values and returns a single output value (decision), and these input and output values can be discrete or continuous.

Larose (2005) states that a decision tree is an assortment of decision nodes, coupled by branches, which spread down from the root node until terminating in leaf nodes. Mitchell (1997) adds to this by stating that decision trees provide classification to an instance by sorting them down the tree from the root node to some leaf node. Every node postulates a test of some attribute of the instance, and each branch descending from that node corresponds to one of the possible values for this attribute. Russel and Norvig (2010) identify that a decision tree performs a sequence of tests to reach its decision. Every internal node in the tree relates to a test of the value of one of the input attributes, A_i, and the branches from the node are labelled with the possible values of the attribute, $A_i = v_{ik}$. Lastly, each leaf node in the tree specifies a value to be returned by the function.

Mitchell (1997) describes that a general learning decision tree algorithm makes use of a top-down, greedy search through the space of possible decision trees. It does this by starting with the root node which is statistically found as the attribute which best alone classifies the training examples. Next, a descendent of the root node is created for each possible value of this attribute and training examples are sorted to the appropriate descendent node, after which this procedure is repeated. This greedy search finds a suitable decision tree, however, the algorithm never backtracks to re-evaluate previous selections. Russel and Norvig (2010) add that there is no way to efficiently search through the trees. Larose (2005) identifies that training data needs to be rich and varied, providing the algorithm with a healthy cross section of types of records for which classification may be needed in the future. Mitchell (1997) continues that decision trees allow for the training data to contain errors or missing attribute values, although Russel and Norvig (2010) state that decision trees are bound to make some mistakes for cases where the tree has not seen examples.

Mitchell (1997) states that a vital part of the algorithm is to identify which attribute to test at each node in the tree. He states that the most useful attribute for classifying the examples should be selected. Larose (2005) adds that the attributes for each node should be selected based on their purity, or as Mitchell (1997) states, how well a given attribute separates the training examples according to their target classification. Both Mitchell (1997) and Larose (2005) identify *Information Gain* from the $C4.5$ algorithm as one of the best methods to achieve this. In order to understand information gain, *Entropy* needs to be introduced. Entropy characterises the impurity/purity of an random assortment of examples. Entropy can be mathematically represented as in Equation 2.5.6.

$$\text{Entropy}(S) \equiv \sum_{i=1}^{c} -p_i \log_2 p_i \tag{2.5.6}$$

where:

p_i $\equiv$ Proportion of S belonging to class i.

S is a collection of examples.

Now, Information Gain identifies the effectiveness of an attribute in classifying the training data and it is the expected reduction in entropy caused by partitioning the examples according to this attribute, which is mathematically represented as in Equation 2.5.7.

$$\text{Gain}(S, A) \equiv \text{Entropy}(S) - \sum_{v \in \text{Values}(A)} \frac{|S_v|}{|S|} \text{Entropy}(S_v) \tag{2.5.7}$$

where:

$\text{Entropy}(S)$ is defined in Equation 2.5.6.

$\text{Values}(A)$ is the set of all possible values for attribute A.

S_v is the subset of S for which attribute A has a value v.

For example, the *Outlook*, *Temperature*, *Humidity*, and *Wind* are four attributes measured to decide whether to go play sport outside or not. Their individual gains are calculated, where the *Outlook* gain is the largest which identifies it as the attribute which best predicts the target attribute 'to go play sport outside'. Of 14 training examples, *Outlook* has nine positive examples and five negative examples (meaning nine examples result in going outside, and five examples result in not going outside). Looking down the *Sunny* branch, there are two positive examples and three negative examples. Down the *Overcast* branch, there are four positive examples and no negative examples, thus it results in a leaf node saying 'yes' go play sport outside. This can be seen in Figure 2.24.

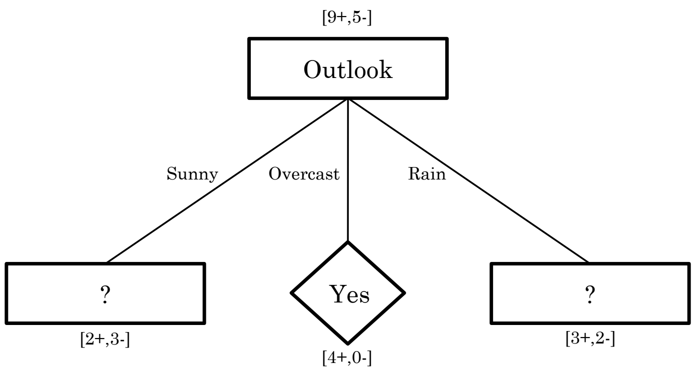


Figure 2.24: Learning decision tree example

In order to identify which attribute should be tested next when following the *Sunny* branch, the gains of the remaining attributes should be calculated relative to the new subset of examples; these three gains can be seen below.

$\text{Gain}(S_{\text{Sunny}}, \text{Humidity}) = 0.970$

$\text{Gain}(S_{\text{Sunny}}, \text{Temperature}) = 0.570$

$\text{Gain}(S_{\text{Sunny}}, \text{Wind}) = 0.019$

The *Humidity* gain is the largest, and thus it is the next attribute that should be tested down the *Sunny* branch.

After this process is completed, validation of the tree should be performed to identify if over-fitting has occurred. Over-fitting is described by Murty and Devi (2011) and Russel and Norvig (2010) as when there is a unique path through the tree for every pattern in the training set, and this occurs when the algorithm generates a large tree when there is actually no pattern found. Russel and Norvig (2010) state that over-fitting is more likely to occur as the hypothesis space and the number of input attributes grow and is less likely to occur as the number of training examples are increased. Lastly, Murty and Devi (2011) and Russel and Norvig (2010) both state that pruning is a solution to the problem of over-fitting by eliminating nodes of attributes that are clearly not relevant.

2.5.6 Summary and comparison of the modelling techniques

As discussed earlier, ANN are tremendously powerful for tasks such as information processing, learning and adaption as well as being one of the most prevalent and effective forms of learning systems.

Fuzzy sets offer a meaningful and powerful representation of measurement uncertainties and fuzzy sets provide a mathematical approach to characterise vagueness and fuzziness in humanistic systems. Fuzzy systems are primarily used in deductive reasoning.

SVM is a binary classifier which abstracts a decision boundary in multi-dimensional space using an appropriate sub-set of the training set of vectors.

A HMM can be used to characterise classes of patterns, where each pattern is viewed as a sequence of states. The Markov chain is hidden and thus not observable, however what is available to the observer is another stochastic process, linked to the Markov chain.

Lastly, decision tree learning is one of the most widely used and practical methods for inductive inference. It is a method for approximating discrete-valued functions that is robust to noisy data and capable of learning disjunctive expressions, whereby creating a tree of decisions, different paths followed will result in different outcomes.

The model to be used in this study will see each accident or time step as a pattern, thus a generalised pattern will be determined, which links all the influencing factors to the outcome and then all the consecutive patterns will be plotted versus time. As such, a pattern recognition sample data set was obtained to test which technique will be best suited for the application. The data set obtained contained 214 entries, each entry had nine input attributes and two output classifications. The input attributes were, *Refractive Index*, *Sodium*, *Magnesium*, *Aluminium*, *Silicon*, *Potassium*, *Calcium*, *Barium*, and *Iron* and the output classifications were, *Non-window glass* or *Window glass*. 163 of the examples are classified as non-window glass, and the remaining 51 examples are classified as window glass.

Firstly, it must be noted that fuzzy logic is a method for extracting definite results from vague or uncertain values, however, it does not connect multiple factors to determine an output. Secondly, a HMM is time dependant and searches for patterns dependant on time and not on patterns between multiple factors, so although this process may work with accident data that is based on time, it will not identify a pattern connecting the influencing factors together. This leaves us with three remaining techniques, namely, ANN, SVM, and learning decision trees. These three methods were all tested with the same glass classification data and the results are presented below.

The ANN was created with the nine inputs, seven hidden nodes and the two output nodes. The hidden layer nodes and output layer nodes all used sigmoid activation functions. Then the data was split such that 65% of the data was used for training the model, 25% of the data was used for validating the model, and 10% of the data was used for testing the model. Table 2.6 presents the associated Mean Square Error (MSE) and percentage errors for the three sets of data, as well as the totals. After the network was suitably trained to the

Table 2.6: ANN MSE and percentage error

	MSE	**% E**
Training	$1.79747(10^{-2})$	2.15827
Validation	$2.09714(10^{-2})$	0
Testing	$2.36972(10^{-3})$	0
Total	$1.71996(10^{-2})$	1.40186

errors seen in Table 2.6, the network was run with all 214 examples in the data set. This yielded 211 of the examples being correctly classified and three examples misclassified. The confusion matrix for this technique is plotted in Figure 2.25, it shows that one non-window glass example was classified as window glass, two window glass examples were classified as non-window glass, 162 non-window glass examples were correctly classified, and 49 window glass examples were correctly classified. Figure 2.25 also shows that the overall error for the ANN is 1.40%.

		True		
		Non-window glass	**Window glass**	**Total**
Prediction	**Non-window glass**	**162**	**2**	**98.80%** **1.20%**
	Window glass	**1**	**49**	**98.00%** **2.00%**
	Total	**99.40%** **0.60%**	**96.10%** **3.90%**	**98.60%** **1.40%**

Figure 2.25: Glass classification confusion matrix for Artificial Neural Networks (ANN) method

Next, the SVM technique was tested using the same data set. The data was split such that 70% was used for training and 30% was used for testing. Firstly, the model parameters need to be set; from using the 10−fold cross validation method to minimise error, the optimal values for the cost function ($C = 1.0$) and gamma ($\gamma = 0.1$) were found. Next, the model was trained with the training data, using a radial kernel function, and the two optimal parameters calculated above. Of the 150 training examples, 40 are identified as support vectors (22 classifying non-window glass and 18 classifying window glass). After this, the testing data was run through the model, Table 2.7 presents the percentage errors associated to the training, testing and total data. After the network was trained suitably, the model was run with all 214

Table 2.7: SVM percentage error

	% E
Training	2.000
Testing	3.125
Total	2.340

examples in the data set. This yielded 209 of the examples being correctly classified and five examples misclassified. The confusion matrix for this technique is plotted in Figure 2.26, it shows that two non-window glass example were classified as window glass, three window glass examples were classified as non-window glass, 161 non-window glass examples were correctly classified, and 48 window glass examples were correctly classified. Figure 2.26 also shows that the overall error for the SVM is 2.34%.

		True		
		Non-window glass	**Window glass**	**Total**
Prediction	**Non-window glass**	**161**	**3**	**98.17%** **1.83%**
	Window glass	**2**	**48**	**96.00%** **4.00%**
	Total	**98.77%** **1.23%**	**94.12%** **5.88%**	**97.66%** **2.34%**

Figure 2.26: Glass classification confusion matrix for Support Vector Machine (SVM) method

Lastly, a learning decision tree was created using all 214 examples and the C4.5 algorithm which discerns between attribute importance dependant on the maximum information gain. A binary decision tree was created, implying that each attribute could only have two branches, thus each attribute was split according to its mean value as can be seen in Figure 2.27 which presents the decision tree created, the 'W' classifies window glass and 'NW' classifies non-window glass. Then the decision tree was pruned and the result after pruning can be seen in Figure 2.28. After the decision tree was created, all 214

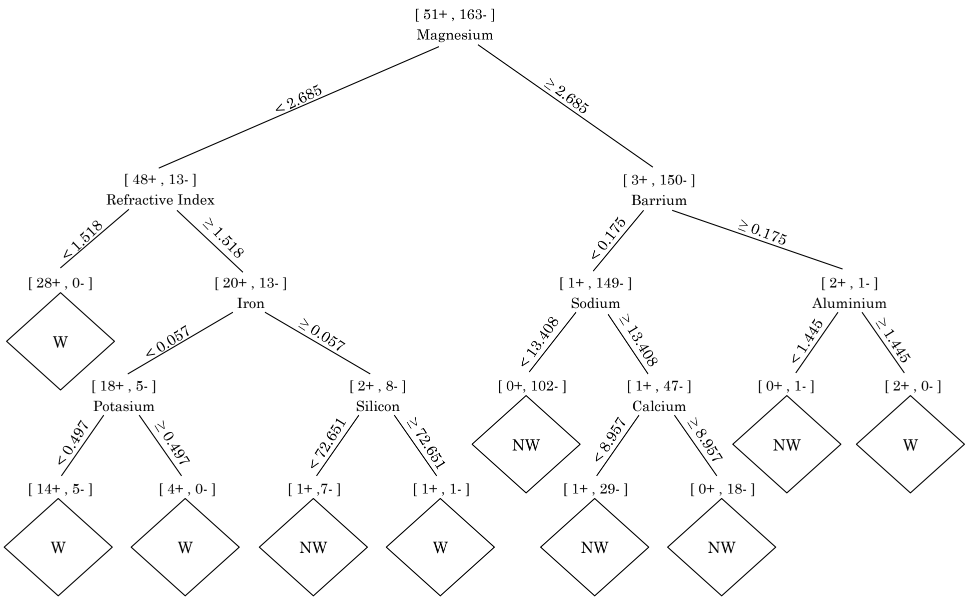


Figure 2.27: Decision tree created for glass classification example

examples in the data set were run through the decision tree. This yielded 206 of the examples being correctly classified and eight examples misclassified. The confusion matrix for this technique is plotted in Figure 2.29, it shows that six non-window glass example were classified as window glass, two window glass examples were classified as non-window glass, 157 non-window glass examples were correctly classified and 49 window glass examples were correctly classified. Figure 2.29 also shows that the overall error for the decision tree is 3.74%.

In conclusion, from the three techniques analysed above, it can be seen that the ANN has the lowest total error. Also, further calculations were performed on all three techniques with the data from their confusion matrices to ensure that an ANN is the best technique to use. The calculations used to gauge the modelling techniques are, True Positive Rate (TPR) (also known as sensitivity), True Negative Rate (TNR) (also known as specificity), Positive Predictive Value (PPV) (also known as precision), Negative Predictive Value (NPV), average accuracy, average reliability and overall accuracy. Appendix B presents the equations used for all the calculations. Table 2.8 displays the results from all the calculations. As can be seen from Table 2.8, ANN is the best overall technique and the most accurate, thus it is the modelling technique chosen to be used in the model to be created.

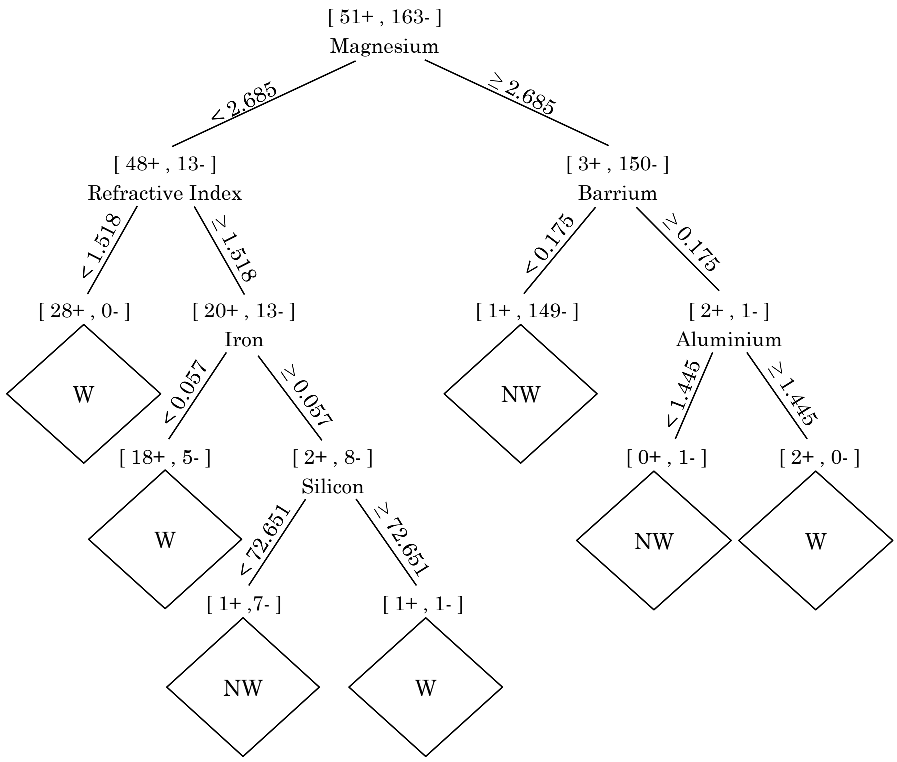


Figure 2.28: Decision tree after pruning

		True		
		Non-window glass	**Window glass**	**Total**
Prediction	**Non-window glass**	**157**	**2**	**98.74%** **1.26%**
	Window glass	**6**	**49**	**89.09%** **10.91%**
	Total	**96.32%** **3.68%**	**96.08%** **3.92%**	**96.26%** **3.74%**

Figure 2.29: Glass classification confusion matrix for learning decision tree method

2.6 Chapter 2 Concluding Remarks

In conclusion, from the literature study, safety is identified as crucially important in all forms of industry. Additionally, there are very few safety models available which predict the continuous risk of accidents occurring in the future. Furthermore, risk is found to be a part of everyday life and the risk is higher

Table 2.8: Comparison of modelling techniques

	ANN	**SVM**	**Decision Tree**
TPR	0.9878	0.9817	0.9874
TNR	0.9800	0.9600	0.8909
PPV	0.9939	0.9877	0.9632
NPV	0.9608	0.9412	0.9608
Avg. Accuracy	0.9775	0.9645	0.9620
Avg. Reliability	0.9840	0.9709	0.9392
Overall Accuracy	0.9860	0.9766	0.9626

in industries such as mining. Moreover, risk has a direct effect on occupational safety and thus is essential to keep in control. Also, the measurable influential factors that lead to accidents are identified as the time of the day, the temperature and humidity, the noise levels, the production rate, the shift length and the occupation. Lastly, five modelling techniques were explored and evaluated, resulting in identifying the ANN as the best modelling technique which is used for the model developed in this study.

Chapter 3

Design And Construction Of The Model

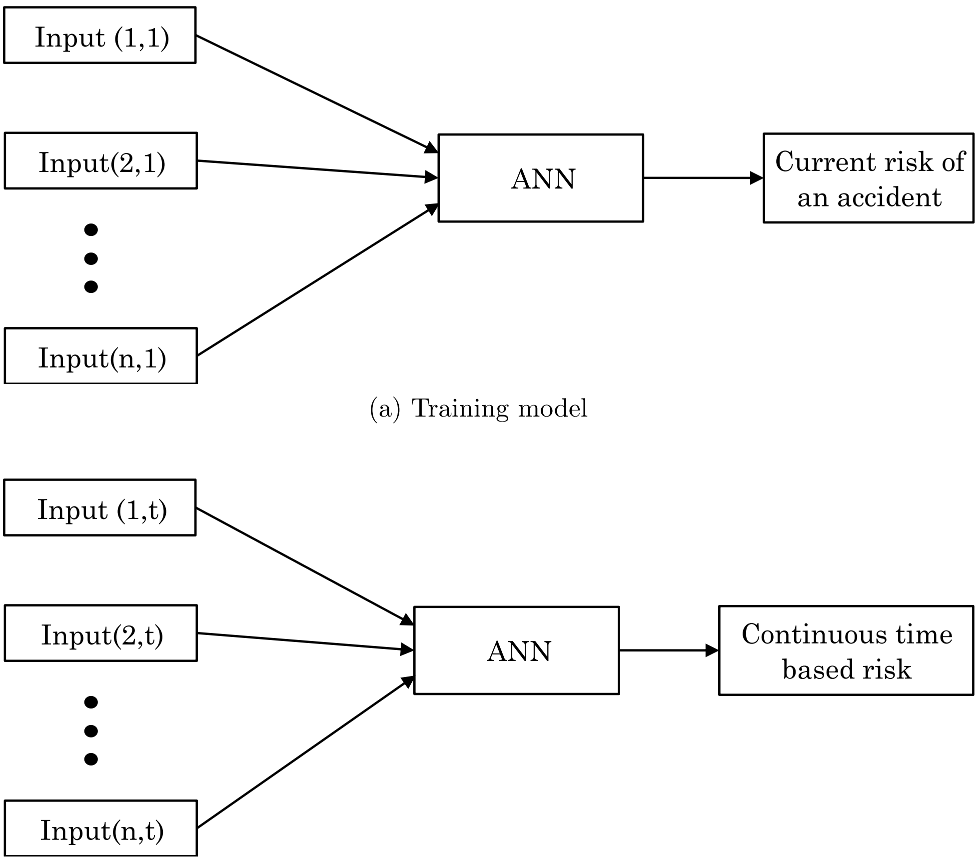
3.1 Introduction

From the previous chapter it was identified that an Artificial Neural Networks (ANN) model with a Multilayer Perceptron (MLP) network configuration will be used for the model. The ANN model will be trained with the back-propagation algorithm and after the model is built, trained, and validated, the continuous risk of accidents occurring will be calculated. This chapter is closely linked with the next chapter, as this chapter covers the mathematics behind ANNs, the data analysis, the model design, and lastly the setup of the model. Then the next chapter goes about training and validating the model.

3.2 Model Overview

The model can be created in three separate parts, the first being the data manipulation for the network, which is presented later in this chapter. The second part involves the ANN model which links all the inputs to the output (training the network), which is presented in the next chapter. The third part involves use of the model to predict the continuous risk of an accident occurring into the future (running the model) for the year the network was trained with, as well as for the subsequent year in order to validate the networks accuracy, which is presented in the next chapter as well.

The nine influential inputs to the model identified in the literature study are, *Location*, *Occupation*, *Noise level*, *Time of day*, *Time into shift*, *Lighting*, *Temperature*, *Humidity* and *Production rate*. The first part of the model manipulates these values to prepare them as inputs for training the network. The next part takes these inputs, runs them through the ANN model to calculate the current risk of accidents occurring. Next, the third part of the model takes the ANN model with its associated parameters and uses the calculated current risk of accidents occurring as well as estimates of future attribute values, in order to predict the continuous risk of accidents occurring in the future, within certain confidence intervals. This model described above is schematically presented in Figure 3.1. Both the training and running models have *1-to-n* inputs,



(a) Training model

(b) Running model

Figure 3.1: Overview of the model to be developed

however, the training model takes a vector of inputs at each accident which results in a single risk value, whereas the running model takes a matrix of these inputs separated by a certain time interval which results in a continuous time based risk profile. The section to follow discusses the mathematics behind the ANN used in the model.

3.3 Artificial Neural Networks (ANN) Mathematics

The work covered in this section is based primarily on five separate texts written by Larose (2005), Russel and Norvig (2010), Nelles (2001), Page *et al.* (1993), and Mitchell (1997). Figure 3.2 presents a one hidden layer MLP ANN which will be referred to during the explanations to follow, and a description of the variables used can be found in the nomenclature at the beginning of this thesis.

3.3.1 Network architecture

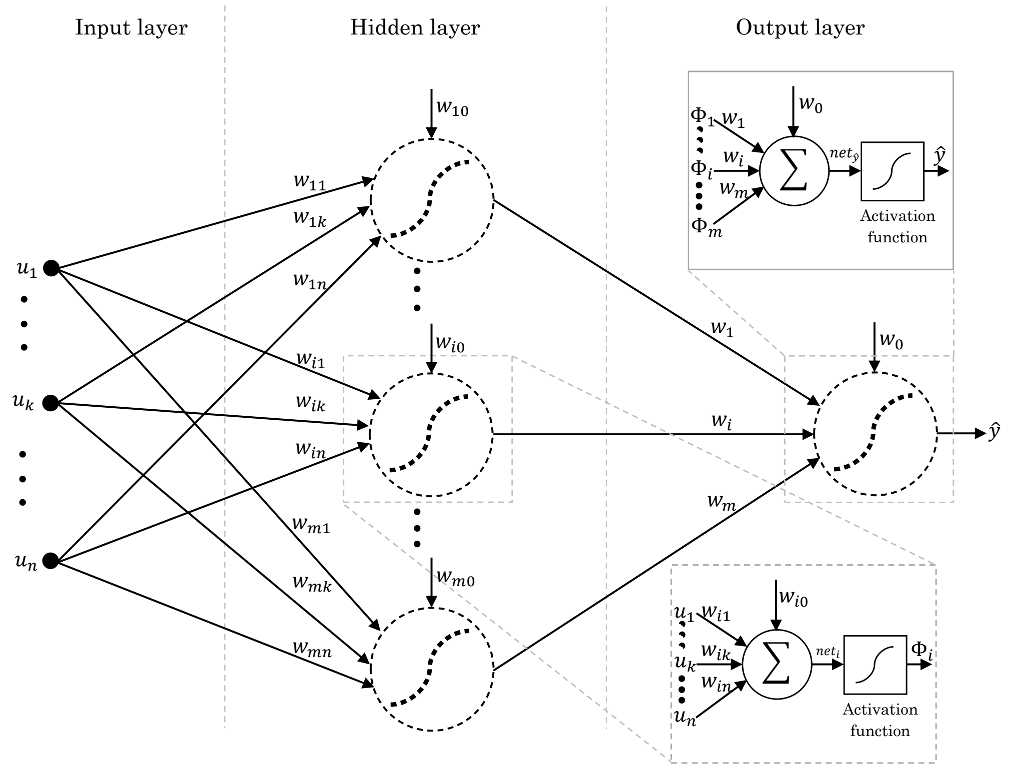


Figure 3.2: Schematic of a Multilayer Perceptron (MLP) Artificial Neural Networks (ANN) model with one hidden layer (adapted from Nelles (2001))

Firstly, from the figure, it can be seen that there are three layers (Input, Output, and Hidden layer). The input and output layers always only consist of one layer each, however, they can have multiple nodes within each layer. Generally, the input layer has as many nodes as the number of attributes measured in the training data and occasionally with an extra node for a bias term. The output layer can also have multiple nodes, although they often only have a single node, as depicted in Figure 3.2. Moving to the middle, the hidden layer can have multiple layers as well as multiple nodes within each layer, however, choosing how many hidden layers to use has no logical steps. If the data is linearly separable, then an ANN is not required and no hidden layers are needed. Furthermore, with a single sufficiently large hidden layer representing any continuous function of inputs is possible, and with two hidden layers even discontinuous functions are representable. Thus, generally for most applications one hidden layer is sufficient. Furthermore, the increase in performance of the ANN is minor when an additional hidden layer is coupled, all-the-while the complexity is drastically increased. With regards to choosing how many nodes to use within every hidden layer, the rule of thumb is that in the hidden layer the quantity of nodes is usually between how many nodes there are in the input layer and the how many nodes there are in the output layer. Some texts take the mean value of the quantity of nodes in the input and output layers, while some texts take two thirds of the sum of the input and output nodes. Irrespective of how many nodes are chosen for the hidden layer, if there are too many modes in this layer, then after training the model, the redundant nodes can be removed using a technique known as pruning. However, if there are too few hidden layer nodes, then the network may never converge. Thus, it is imperative to start off with sufficient or too many nodes rather than too few hidden layer nodes. If over-fitting occurs, the quantity of nodes in the hidden layer can be reduced; alternatively, if training accuracy is lower than acceptable, then the quantity of hidden layer nodes can be increased. Over-fitting is the opposite of generalisation, it is when the network has too many parameters relative to the number of examples and then the network will have poor predictive performance and will exaggerate minor fluctuations in the data.

The structure of the hidden layer and output nodes is different to that of the input layer, because the input layer nodes only take the input data and pass it on to the hidden layer nodes, whereas the hidden layer and output layer nodes both have a summation function and an activation function.

3.3.2 Inputs

Input data should be normalised such that the input value (u_k) multiplied by the value of the weight connecting it to the hidden layer (w_{ik}), for all inputs and weights, are roughly in the similar range such that no input is more dominant. All attribute values of the input data entering an ANN must take a value between zero and one. For continuous variables the *min-max normalisation* method can easily transform the data to a value between zero and one as can be seen in Equation 3.3.1.

$$X^* = \frac{X - \min(X)}{\text{range}(X)} \tag{3.3.1}$$

However, categorical variables such as *gender* is more problematic and cannot be normalised by using Equation 3.3.1, although, indicator variables can be used in these cases. For example, the values of male, female or unknown can be assigned to the gender attribute. Therefore, indicator variables can be created for male and female, and then every entry would contain a value for each. Thus, entries for males would assume a value of one for male and zero for female, whereas entries for females would contain a value of zero for male and one for female, and lastly unknown entries would assume values of zero for female and zero for male.

3.3.3 Outputs

With respect to the output, a continuous value between zero and one is always returned by the output nodes of the ANN. With clearly ordered classes, single output nodes are generally used. For example when classifying if a loan can be given,

- ✧ If $0 \leq \hat{y} < 0.50$, classify *loan denied.*
- ✧ If $0.50 \leq \hat{y} < 0.90$, classify *loan approved.*
- ✧ If $\hat{y} > 0.90$, classify *offer larger loan.*

When categories are unordered, multiple output nodes can be used. For example, *marital status* has six classes, these are *single*, *married*, *divorced*, *separated*, *widowed* and *unknown*. This type of output is known as *1-of-n* output encoding, which has one output node per output category of the target variable, then classification for that particular record is based on the output node containing the maximum value. A measure of confidence (the difference between the highest and second highest) is an advantage the *1-of-n* output encoding offers, and classifications with low confidence can be highlighted for further clarification. After classification, an output (between zero and one) can always be transformed back into a predicted value by inverting the *min-max normalisation*, which is known as denormalisation.

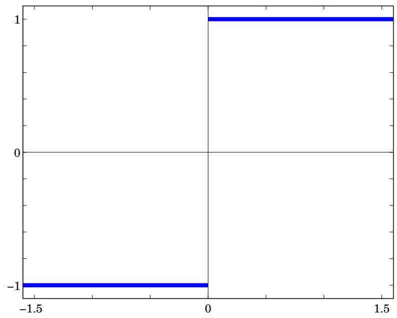
3.3.4 Node mathematics

As discussed in the previous chapter, there are four predominant activation functions, namely the sigmoid, the hyperbolic tan, the threshold and the hard-limiter, which can be seen in Figure 3.3. Of these four activation functions, the sigmoid is the most popular function since dependent on the input value it conglomerates close to linear behaviour, curvilinear behaviour and close to constant behaviour. The sigmoid activation function is also known as the logistic function, which is described in Equation 3.3.2.

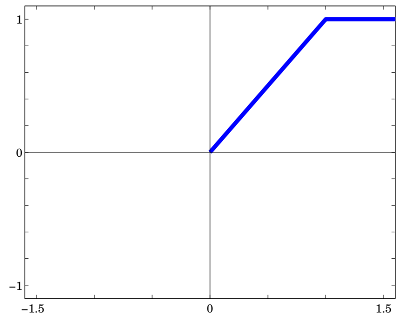
$$y = \frac{1}{1 + e^{-x}} \tag{3.3.2}$$

When an ANN operates in feed-forward mode, every node receives an input from upstream nodes (eg. the hidden node receives an input from the input node) and delivers the output to downstream nodes (eg. the hidden nodes send its output to the output node). The input values (u_k) get passed on to the hidden nodes via the weighted connections (w_{ik}). The hidden node firstly sums these inputs (net_i) as in Equation 3.3.3.

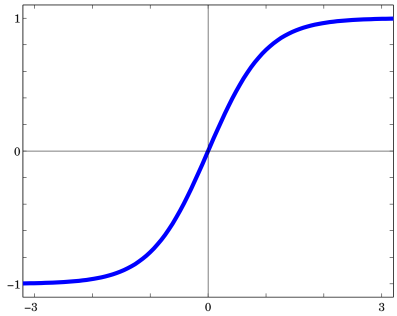
$$\text{net}_i = \sum_{j}^{n} w_{ij} u_j \tag{3.3.3}$$



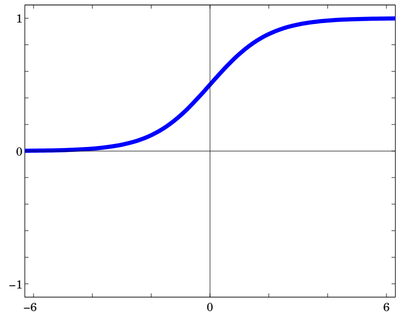
(a) Hard limiter



(b) Threshold



(c) Tanh



(d) Sigmoid

Figure 3.3: Graph of activation functions

After this, net_i is passed on to the activation function, as in Equation 3.3.4.

$$\Phi_i = \frac{1}{1 + e^{-\text{net}_i}} \tag{3.3.4}$$

This activation function output, Φ_i, is then passed on to the next hidden layer where the same procedure takes place, although the input to the next hidden layer is Φ_i now and not u_k as before, or if there are no more hidden layers Φ_i is then passed on to the output layer.

3.3.5 Network training

In order to obtain all the weights within the network, the network needs to be trained with multiple examples. Furthermore, the most common method of training the network is back-propagation using the gradient descent optimisation method to minimise the error function as seen in Equation 3.3.5. The error function used in the optimisation is the sum of squared errors, where the squared prediction errors (difference between actual output values and target output values) are added across every output node and every record in the set of training examples. Equation 3.3.5 describes mathematically how the sum of squared errors is calculated.

$$E(\vec{\mathbf{w}}) = \frac{1}{2} \sum_{d \in D} \sum_{k \in O} (t_{kd} - o_{kd})^2 \tag{3.3.5}$$

where:

d is the training example.

D is the set of training examples.

k is the k^{th} output.

O is the set of output nodes in the network.

t_{kd} is the target value of the k^{th} output and d^{th} training example.

o_{kd} is the output value of the k^{th} output and d^{th} training example.

If there is only one output node, Equation 3.3.5 would reduce to,

$$E(\vec{\mathbf{w}}) = \frac{1}{2} \sum_{d \in D} (t_d - o_d)^2 \tag{3.3.6}$$

3.3.6 Gradient descent method

A problem arises with setting the model weights such that the sum of squared errors is minimised, and this is where the gradient descent method comes in. In order to lessening the error function the gradient descent method identifies the direction that each weight should be adjusted. The gradient descent method can only be used if the output of the nodes is differentiable, thus the sigmoid function is a very popular activation function, as it is differentiable. Assuming there is a vector of r weights $\vec{\mathbf{w}} = w_1, w_2, ..., w_r$ in an ANN, the vector derivative is the gradient of the error function with respect to the weights vector $\vec{\mathbf{w}}$ is the, as presented in Equation 3.3.7, it is the partial derivative of the error function with respect to each of the weights.

$$\nabla E(\vec{\mathbf{w}}) = \left[\frac{\partial E}{\partial w_1}, \frac{\partial E}{\partial w_2}, ..., \frac{\partial E}{\partial w_r} \right] \tag{3.3.7}$$

In order to demonstrate how the gradient descent method operates, assume an instance when only one weight, w_1 is used. As can be seen in Figure 3.4, the error function is plotted versus an assortment of weight w_1 values. The values of w_1 that minimise the error function are sought after. w_1^* depicts the optimal value for weight w_1 and in order to move nearer to this optimal value from the current position on the graph, Equation 3.3.8 can be used.

$$w_{\text{new}} = w_{\text{current}} + \Delta w_{\text{current}} \tag{3.3.8}$$

where:

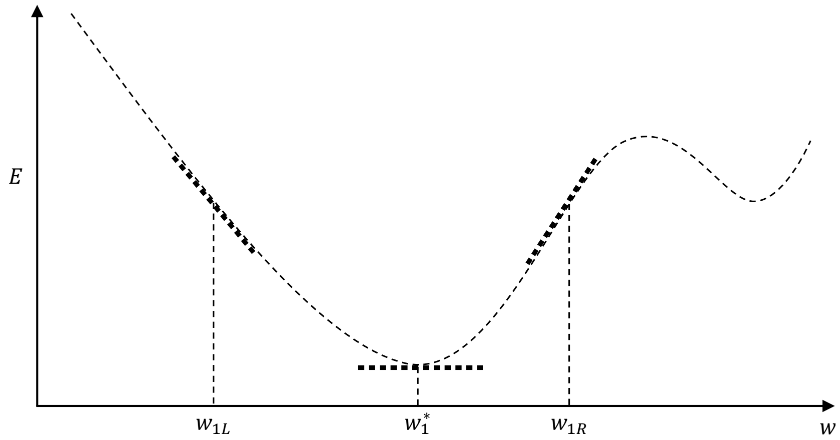


Figure 3.4: Finding the direction for the weight adjustment using the gradient of the error function with respect to weight w_1

$\Delta w_{\text{current}}$ is the change in current location of w.

For example, if in Figure 3.4 the current weight w_{current} is near $w_{1\text{L}}$, then the weight needs to be increased to move w_{current} closer the optimal point w_1^*. Similarly, if the current weight w_{current} is near $w_{1\text{R}}$, then the weight needs to be decreased to move w_{current} closer the optimal point w_1^*. In order to achieve this, the partial derivatives of the error with respect to the current weight are required, because the derivative $\partial E/\partial w_1$ is just the gradient of the error function at w_1. The gradient is negative for values of w_1 close to $w_{1\text{L}}$, and the gradient is positive for values of w_1 close to $w_{1\text{R}}$. Thus the adjustment direction for w_{current} is negative the sign of the derivative of the error function at the current position $(-\text{sign}(\partial E/\partial w_{\text{current}}))$.

The next step is to set how far the adjustment should move, since the direction is already identified. If the magnitude of the derivative is used, when the gradient is steep then large adjustments are used, and when the gradient is flatter the step size will be smaller, which intuitively makes sense to do. Finally, a learning rate η is commonly multiplied to the derivative. This learning rate is a positive constant varying between zero and one that scales the step size. Thus the resulting change in location of w is $\Delta w_{\text{current}} = -\eta(\partial E/\partial w_{\text{current}})$.

3.3.7 Back propagation

As stated earlier, the algorithm for back-propagation uses the prediction error for a particular example and filters the error back through the network, which assigns partitioned responsibility for the error to the various connections. Thereafter, these connections weights are adjusted to reduce the error using the gradient descent method. When making use of a *sigmoid activation function* and the gradient descent optimisation technique, the back-propagation rule for an ANN can be rewritten as,

$$w_{ik,\text{new}} = w_{ik,\text{current}} + \Delta w_{ik} \tag{3.3.9}$$

where:

$$\Delta w_{ik} = \eta \delta_i x_{ik}.$$

where:

η signifies the learning rate.

x_{ik} signifies the k^{th} input to node i.

δ_i signifies the responsibility for a particular error belonging to node i.

Appendix A derives the error responsibility δ_i, and can take two forms conditional on the layer the node resides in. These two forms are as follows,

$$\delta_i = \begin{cases} o_i(1-o_i)(t_i-o_i) & \text{for output layer nodes.} \\ o_i(1-o_i)\sum_{downstream} w_{ik}\delta_i & \text{for hidden layer nodes.} \end{cases} \tag{3.3.10}$$

where:

o_i is the output computed by node i.

t_i is the target output for node i.

$\sum_{\text{downstream}} w_{ik}\delta_i$ refers to the weighted sum of the error responsibilities for the nodes downstream from the particular hidden layer node.

Earlier it was established that the input attribute values must be normalised to values between zero and one, this is because large non-normalised values would dominate the weight adjustments, and therefore the error propagation throughout the network would be overwhelmed and learning would be affected.

The ANN algorithm would normally proceed to step through every record in the training data set and after each record adjust the weights accordingly. This weight updating after each record is known as online back-propagation. This performs as a barrier stopping the function getting caught in a local minimum, however, a momentum term can always be added to assist in skipping some local minima in an attempt to find the global minimum of the error function $E(\vec{\mathbf{w}})$.

3.3.8 Momentum

Adding momentum to the back-propagation algorithm can be used to streamline the training process. Momentum α $(0 < \alpha < 1)$ is a constant which essentially adds momentum which helps from one iteration to the next to keep the ball rolling in the same direction. This has the effect of keeping the ball rolling through small local minima or along flat regions. It gradually increases the step size in areas when there is no change in the gradient, and thus convergence is reached quicker. Mathematically, this changes Equation 3.3.9 to,

$$w_{ik,\text{new}} = w_{ik,\text{current}} + \Delta w_{ik,\text{current}} \tag{3.3.11}$$

where:

$$\Delta w_{ik,\text{current}} = \eta \delta_i x_{ik} + \alpha \Delta w_{ik,\text{previous}}$$

where:

η represents the learning rate.

δ_i represents the responsibility for a particular error belonging to node i.

x_{ik} signifies the k^{th} input to node i.

α represents the momentum $(0 < \alpha < 1)$.

$\Delta w_{ik,\text{previous}}$ represents the weight update value from the previous iteration.

The algorithm may undershoot the global minimum from a small momentum, α and the algorithm may overshoot the global minimum from a large momentum, α. For example, in Figures 3.5 and 3.6, the weight is initialised at position I, position A and C are local minima, and position B is the global minimum. If the momentum α is small, as in Figure 3.5, the algorithm will easily find the first minimum at position A, however, it may stay stuck in this valley and never make it over the first hill, thus never finding the global optimum. Conversely, if the momentum α is large, as in Figure 3.6, the algorithm will easily get passed the first hill, but it may have too much momentum and overshoot the global minimum at position B, ending up at the local minimum at position C.

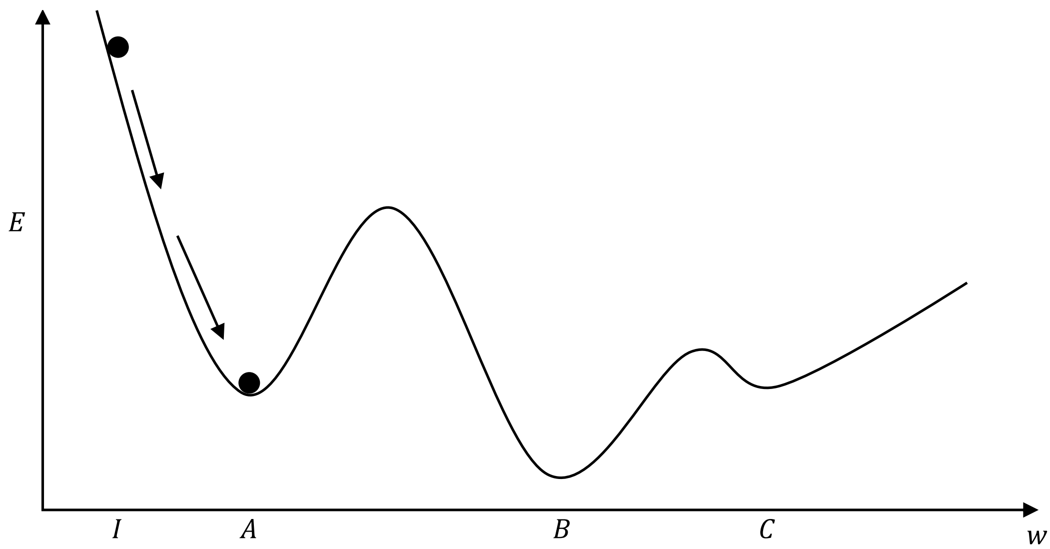


Figure 3.5: The algorithm may undershoot the global minimum from a small momentum, α

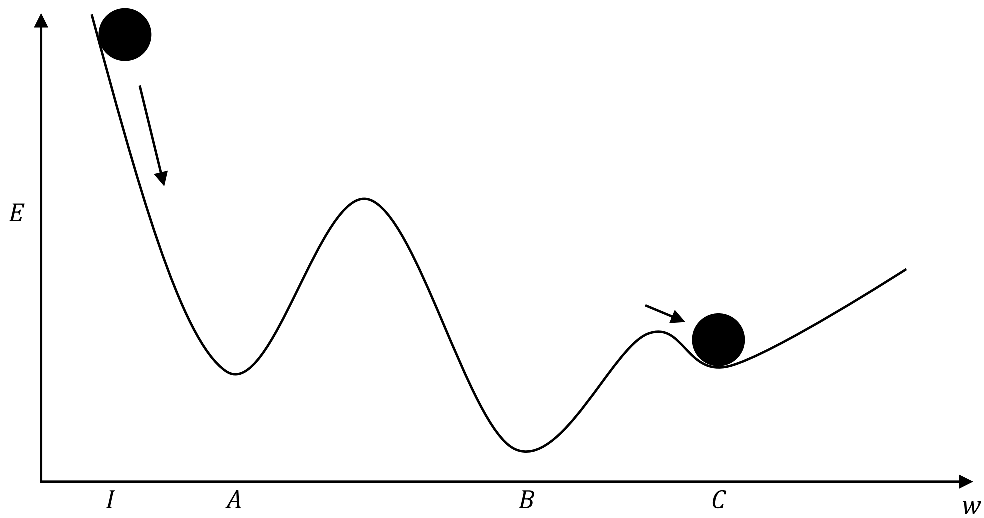


Figure 3.6: The algorithm may overshoot the global minimum from a large momentum, α

3.3.9 Learning rate

Another way to speed up finding the region around the global minimum would be to alter the learning rate η $(0 < \eta < 1)$. It is also a constant that can be used to assist adjusting the weights in the network with the goal of obtaining the global minimum error $E(\vec{\mathbf{w}})$. If a small learning rate is chosen, the adjustments to the weight have a tendency to be rather small and the network takes a long time to converge. However, if a large learning rate is chosen, the adjustments to the weight will tend to be larger and the possibility of overshooting the global minimum is higher. To solve this predicament, the learning rate can start large which allows the network to rapidly approach the general area of the global minimum, after which the learning rate can be gradually decreased to avoid overshooting the minimum. Thus it is important to consider the values used for the learning rate η and momentum α. Generally experimentation is required with numerous values of η and α before the best results can be achieved.

3.3.10 Termination criteria

The back-propagation algorithm would run continuously until a termination criterion is met, of which there are three. The first termination criteria is to stop the training after a certain time period has lapsed or a certain number of iterations of the training data set is achieved, although what is gained with the short training time is at the expense of poor model effectiveness. The second termination criteria is when the error function $E(\vec{\mathbf{w}})$ for the training data is below a certain threshold value. Lastly, the third termination criteria, which is the most effective and popular method, is when the model is trained and then validated with separate unseen data, and the error function $E(\vec{\mathbf{w}})$ for the validation data set is below some threshold value, and if it is not, the process of training and validating is performed again.

3.3.11 Pruning

As discussed earlier, the hidden layer nodal quantity, cannot be predetermined and thus there may be redundant units in the ANN. This makes the generalisation ability lower, the analysis more difficult and is computationally expensive. Furthermore, over-fitting can occur. Pruning is a tool which assists removing the redundant nodes and thus helping the network generalise better, as well as become more efficient. There are two main types of pruning, the first being incremental pruning which starts with just an input and output layer, then the algorithm incrementally increases the size of the ANN and retrains at each increment. Whichever configuration trained the best is assumed to be the optimal network configuration. The second type is selective pruning which begins with an already trained ANN that has some hidden layers and hidden nodes. The selective pruning algorithm chooses hidden nodes to remove that will not affect the error rate of the ANN. Through this method, redundant nodes can be identified and eliminated.

One such selective pruning method removes the nodes from the ANN on the basis of the influence of removing each node on the error, and the ANN is retrained to recover the damage of the removal. This six step algorithm is presented below,

Step 1 Train a large enough ANN until $E \leq E_{\text{threshold}}$.

Step 2 Remove the r^{th} unit virtually and calculate $E^{(r)}$.

Step 3 If every unit is examined by removing it virtually and calculating $E^{(r)}$, then go to Step 4, else go back to Step 2.

Step 4 Remove the a^{th} unit where $E^{(a)}$ is the minimum among all the $E^{(r)}$ values.

Step 5 Retrain the ANN, which has been removed of the a^{th} unit.

Step 6 If $E \leq E_{\text{threshold}}$; then memorise the weights and the structure, and go back to Step 2; else replace the network by the previous one, and finish the steps.

3.3.12 Sensitivity analysis

Once the model is built, trained and pruned if necessary, a sensitivity analysis can be performed in order to identify the relative influence each input attribute has on the output. A sensitivity analysis will take three steps, firstly, new observations must be generated with each attribute equal to its mean value ($\bar{u_1}$, $\bar{u_2}$, ..., $\bar{u_n}$). Secondly, the output for this mean record ($\bar{\hat{y}}$) must be recorded.

Lastly, attribute by attribute the mean values $\bar{u}$ must be varied to the attributes minimum and maximum values, in order to identify the difference in network output for every variation and they can be compared to $\bar{\hat{y}}$. This will find that there are larger effects that certain attributes impose on the network output than other attributes.

3.3.13 Example

For an example of how the ANN model operates in a normal feed-forward method, have a look at Figure 3.7 of a simple ANN with three inputs (1, 2, and 3), one hidden layer with two nodes (A and B), and in the output layer a single node (X) and Table 3.1 which contains the initial values for the weights as well as the data inputs. Firstly, nodes 1, 2 and 3 only pass the inputs

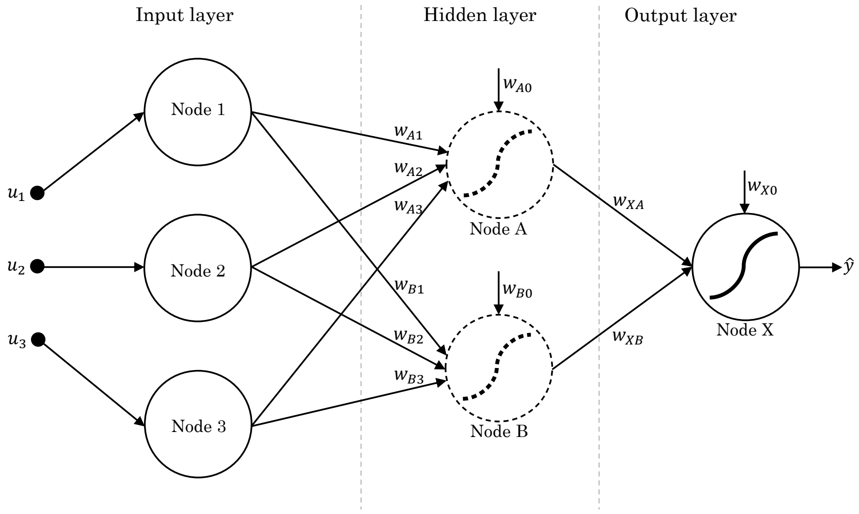


Figure 3.7: Schematic of simple Artificial Neural Networks (ANN)

Table 3.1: Data inputs and initial weight values for ANN in Figure 3.7

Input	**Node A**	**Node B**	**Node X**
$u_0 = 1.0$	$w_{A0} = 0.8$	$w_{B0} = 0.1$	$w_{X0} = 0.9$
$u_1 = 0.8$	$w_{A1} = 0.1$	$w_{B1} = 0.3$	$w_{XA} = 0.2$
$u_2 = 0.4$	$w_{A2} = 0.9$	$w_{B2} = 0.5$	$w_{XB} = 0.4$
$u_3 = 0.1$	$w_{A3} = 0.6$	$w_{B3} = 0.9$	

to nodes A and B. Nodes A and B start by individually producing a linear combination of the node inputs and the connection weights into a single value. Thus for node A this will be,

$$\begin{aligned}\text{net}_A &= \sum_i w_{Ai}u_{Ai} \\ &= w_{A0}u_{A0} + w_{A1}u_{A1} + w_{A2}u_{A2} + w_{A3}u_{A3} \\ &= 0.8(1) + 0.1(0.8) + 0.9(0.4) + 0.6(0.1) \\ &= 1.30\end{aligned}$$

Then, this output is put through the sigmoid activation function before it can be passed on to node X. This activation function step can be seen below,

$$\begin{aligned}\Phi_A &= \frac{1}{1+e^{-1.30}} \\ &= 0.7858\end{aligned}$$

Similarly for node B this will be,

$$\begin{aligned}\text{net}_B &= \sum_i w_{Bi}u_{Bi} \\ &= w_{B0}u_{B0} + w_{B1}u_{B1} + w_{B2}u_{B2} + w_{B3}u_{B3} \\ &= 0.1(1) + 0.3(0.8) + 0.5(0.4) + 0.9(0.1) \\ &= 0.63\end{aligned}$$

$$\begin{aligned}\Phi_B &= \frac{1}{1+e^{-0.63}} \\ &= 0.6525\end{aligned}$$

Next, node X follows a similar procedure, by linearly combining its inputs (Φ_A and Φ_B) with the associated weights (w_{XA} and w_{XB}) of the connections between these nodes. This can be seen below,

$$\begin{aligned}\text{net}_X &= \sum_j w_{Xj}\Phi_i \\ &= w_{X0}u_{X0} + w_{XA}\Phi_A + w_{XB}\Phi_B \\ &= 0.9(1) + 0.2(0.7858) + 0.4(0.6525) \\ &= 1.3182\end{aligned}$$

$$\begin{aligned}\hat{y} &= \frac{1}{1+e^{-1.3182}} \\ &= 0.7889\end{aligned}$$

As can be seen, the network output is $\hat{y} = 0.7889$, assuming that the target output value was $t = 0.7$, and the learning rate is $\eta = 0.6$, then the error $E = 0.5(0.7 - 0.7889)^2 = 0.00395$. Then in order to minimise this error, the network weights must be adjusted by applying the back-propagation algorithm. The weights after each record are updated which is known as online back-propagation.

Firstly, the error responsibility δ_x for the output node X is calculated as,

$$\begin{aligned}\delta_X &= o_x(1-o_x)(t_x-o_x)\\ &= 0.7889(1-0.7889)(0.7-.7889)\\ &= -0.0148\end{aligned}$$

Now the bias weight w_{X0} can be adjusted as follows,

$$\begin{aligned}w_{X0,\text{new}} &= w_{X0,\text{current}} + \Delta w_{X0}\\ &= w_{X0,\text{current}} + \eta\delta_X u_0\\ &= 0.9 + (0.6(-0.0148)(1))\\ &= 0.89112\end{aligned}$$

Next, moving upstream to node A, it is a hidden layer node, therefore its error responsibility is,

$$\begin{aligned}\delta_A &= \Phi_A(1-\Phi_A)\sum_{\text{downstream}} w_{ik}\delta_i\\ &= \Phi_A(1-\Phi_A)(w_{XA}\delta_X)\\ &= 0.7858(1-0.7858)(0.2)(-0.0148)\\ &= -0.000498\end{aligned}$$

Now the weight w_{XA} can be adjusted as follows,

$$\begin{aligned}w_{XA,\text{new}} &= w_{XA,\text{current}} + \Delta w_{XA}\\ &= w_{XA,\text{current}} + \eta\delta_X\Phi_A\\ &= 0.2 + (0.6(-0.0148)(0.7858))\\ &= 0.1930\end{aligned}$$

Next, moving to node B, it is a hidden layer node, therefore its error responsibility is,

$$\begin{aligned}\delta_B &= \Phi_B(1-\Phi_B)\sum_{\text{downstream}} w_{ik}\delta_i\\ &= \Phi_B(1-\Phi_B)(w_{XB}\delta_X)\\ &= 0.6525(1-0.6525)(0.4)(-0.0148)\\ &= -0.00134\end{aligned}$$

Now the weight w_{XB} can be adjusted as follows,

$$\begin{aligned}w_{XB,\text{new}} &= w_{XB,\text{current}} + \Delta w_{XB}\\ &= w_{XB,\text{current}} + \eta\delta_X\Phi_B\\ &= 0.4 + (0.6(-0.0148)(0.6525))\\ &= 0.3942\end{aligned}$$

Next, moving upstream to the connections being used as inputs to node A, for weight w_{A0},

$$\begin{aligned} w_{A0,\text{new}} &= w_{A0,\text{current}} + \Delta w_{A0} \\ &= w_{A0,\text{current}} + \eta \delta_A u_0 \\ &= 0.8 + (0.6(-0.000498)(1)) \\ &= 0.7997 \end{aligned}$$

For weight w_{A1},

$$\begin{aligned} w_{A1,\text{new}} &= w_{A1,\text{current}} + \Delta w_{A1} \\ &= w_{A1,\text{current}} + \eta \delta_A u_1 \\ &= 0.1 + (0.6(-0.000498)(0.8)) \\ &= 0.0998 \end{aligned}$$

For weight w_{A2},

$$\begin{aligned} w_{A2,\text{new}} &= w_{A2,\text{current}} + \Delta w_{A2} \\ &= w_{A2,\text{current}} + \eta \delta_A u_2 \\ &= 0.9 + (0.6(-0.000498)(0.4)) \\ &= 0.8999 \end{aligned}$$

For weight w_{A3},

$$\begin{aligned} w_{A3,\text{new}} &= w_{A3,\text{current}} + \Delta w_{A3} \\ &= w_{A3,\text{current}} + \eta \delta_A u_3 \\ &= 0.6 + (0.6(-0.000498)(0.1)) \\ &= 0.59997 \end{aligned}$$

Similarly, weights between the inputs and node B are adjusted to the following values, $w_{B0,\text{new}} = 0.09920$, $w_{B1,\text{new}} = 0.2994$, $w_{B2,\text{new}} = 0.4997$, and $w_{B3,\text{new}} = 0.8999$. The network output initially was $\hat{y} = 0.7889$, however, after training the model, the new network output is $\hat{y} = 0.7858$, and now the error is $E = 0.00368$. This shows that the network output is minimising the error and moving closer to the target output of 0.7. Table 3.2 presents a summary of the changes in parameters after the first iteration from the ANN example.

Table 3.2: Summary of parameter changes from ANN example

	Initial	**Updated**	**% Change**
w_{A0}	0.8	0.7997	−0.0375
w_{A1}	0.1	0.0998	−0.2000
w_{A2}	0.9	0.8999	−0.0111
w_{A3}	0.6	0.59997	−0.0050
w_{B0}	0.1	0.0992	−0.8000
w_{B1}	0.3	0.2994	−0.2000
w_{B2}	0.5	0.4997	−0.0600
w_{B3}	0.9	0.8999	−0.0111
w_{X0}	0.9	0.8911	−0.9867
w_{XA}	0.2	0.1930	−3.5000
w_{XB}	0.4	0.3942	−1.4500
$w_{\hat{y}}$	0.7889	0.7858	−0.3930
w_E	0.00395	0.00368	−6.8354

3.4 Data Analysis

This section covers the gathering of the data required, as well as the analysis of the data with respect to various aspects. This section starts with the data required and the data collected and is then followed by the analysis.

3.4.1 Data required and collected

As can be seen from the literature review, the following is the list of the attribute factors that influence an accident,

- Time of Day
- Temperature
- Humidity
- Noise
- Location
- Production Rate
- Time into Shift
- Occupation
- Lighting

This required accident data was obtained from a platinum mine in South Africa, with the data spanning from 1st January 2009 to the 31st December 2013. A detailed spread sheet of accident data was received from the mine for accidents over this time period, which contained the following attributes associated to each accident,

- Date
- Time
- Injury type
- A description of the accident
- Parent Agency
- Agency
- Occupation
- Task performed during accident
- Body part injured
- Monthly production figures

Furthermore, the South African Weather Service was approached for weather data for the area of the mines location. The data received was also for the period of 1st January 2009 to the 31st December 2013 and it contained the following daily attributes,

- Daily maximum temperature
- Daily minimum temperature
- Daily humidity
- Daily rainfall

All of the analyses to follow distinguishes between the four injury types of the accidents, which are Fatal Injury (FI), Serious Injury (SI), Lost Time Injury (LTI) and Medical Treatment Case (MTC). Firstly, a FI refers to an accident that occurs where an employee loses their life, secondly, a SI refers to an accident that causes a person to be admitted to a hospital for treatment for the injury, thirdly, a LTI refers to an accident that occurs where an employee is injured and has to spend more than one complete day or shift away from work as a result of the accident, and lastly a MTC refers to any injury that is not a LTI, but does require treatment.

Of all the data entries in the spread sheet received, there were 161 different occupations. With so many different occupations, it was not feasible to create separate models for each occupation. Nonetheless, the risk output can be scaled according to a person's occupation on a continuous basis. Additionally, as can be seen in the next section, the organisational units divide the mining operations/occupations into groups that would work sufficiently well for the model. Lastly, the task performed when the accident took place and the body part injured will not be included in the model, as it will unnecessarily complicate the model further, since there are 112 unique tasks being performed and 51 unique body parts injured in the data set received. Therefore, the rest of the attributes received are analysed, which include organisational units, parent agency, rain, humidity, time of day, temperatures, production rate and seasonality. For all the analyses, the y-axis represents the number of accidents and the x-axis represents the attributes possible values.

3.4.2 Organisational units

The data obtained from the mine contained 1307 accidents over the period of 1st January 2009 to the 31st December 2013 which equates to a yearly average of 261 accidents. Table 3.3 shows a breakdown of these accidents over the five years divided into the organisational units which are sections within the mine.

Table 3.3: Raw data split by organisational unit

	2009	**2010**	**2011**	**2012**	**2013**	**Total**
Underground Section	246	122	369	98	222	1057
Smelter Services	2	0	0	0	0	2
Smelter	3	2	2	3	3	13
Services	16	11	3	6	9	45
Engineering	39	25	28	34	19	145
Concentrators	12	4	7	5	9	37
Mining (Surface)	1	1	1	3	2	8
Total	319	165	410	149	264	1307

For the purpose of this model, the duplicate accidents were removed. For example, if 30 people were all exposed to blast fumes at the same time and had to get medical treatment, this corresponded to 30 accidents, however, for the purpose of this model that will be seen as one type of accident. Table 3.4 presents the breakdown of the accidents after all the duplicates had been removed, which resulted in reducing the accidents from 1307 to 741, which equated to a yearly average of 148 accidents.

From this point onwards, all analyses are performed on the data set with the duplicates removed. The number of accidents with respect to the organisational units are analysed, as can be seen in Figure 3.8.

From this plot, it can be seen that the majority of accidents occurred in the underground section, after which the engineering section has a significant number of accidents and thereafter the rest of the organisational units appear to have minimal accidents. Therefore, it was identified that the data-set should be split into three subsets of data, namely, underground section, engineering section, and the remaining units grouped together as one subset named other section. Furthermore, three separate models were created for these three organisational unit groupings, because the risk within each grouping is notably different.

Table 3.4: Raw data split by organisational unit after duplicates were removed

	2009	2010	2011	2012	2013	Total
Underground Section	128	98	112	91	93	522
Smelter Services	1	0	0	0	0	1
Smelter	3	2	2	3	3	13
Services	16	11	2	6	9	44
Engineering	39	20	20	19	19	117
Concentrators	12	4	6	5	9	36
Mining (Surface)	1	1	1	3	2	8
Total	200	136	143	127	135	741

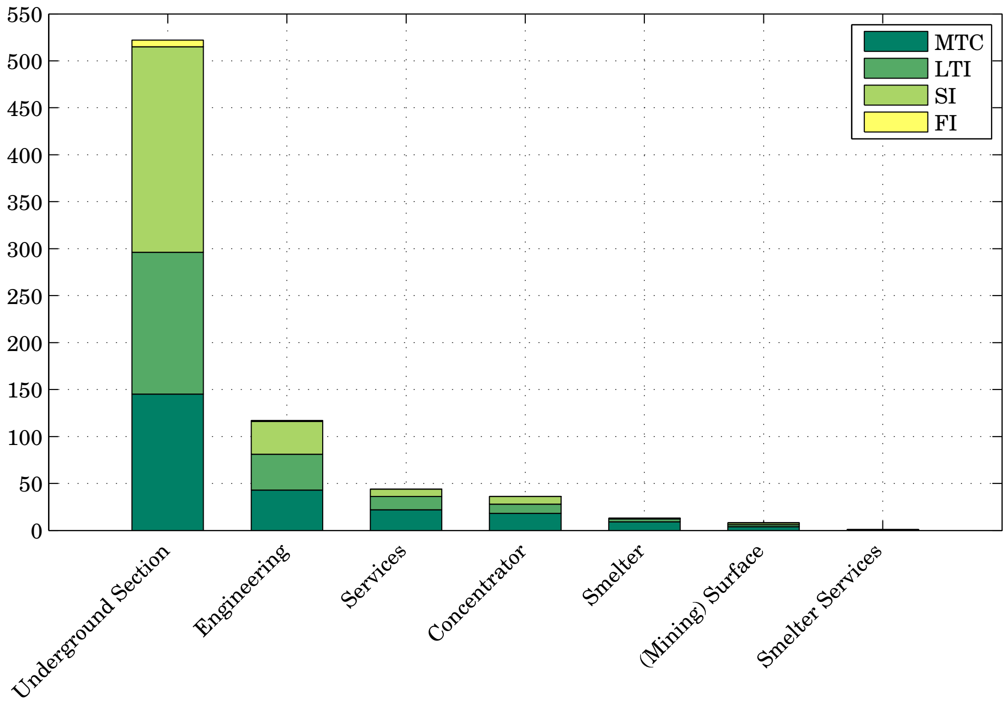
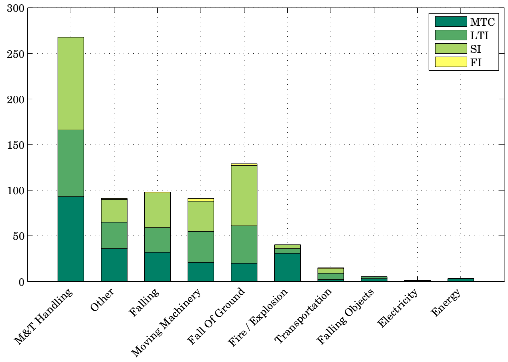


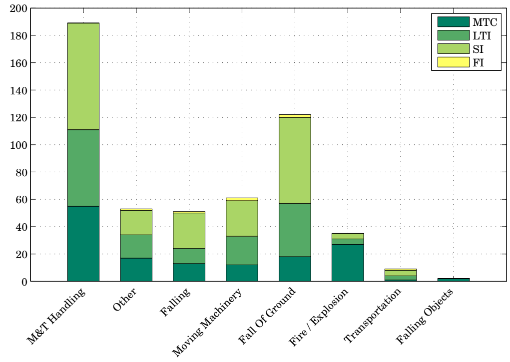
Figure 3.8: Accidents by organisational unit

3.4.3 Parent agency

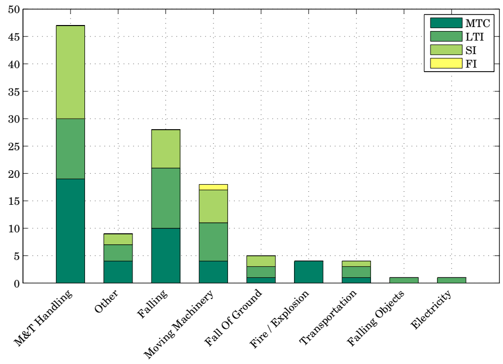
The agency related to each example identifies the cause of the accident, for example, a rolling rock or blasting. The parent agency consists of ten predefined groupings, of which every accident can be classified into at least one category. These ten parent agencies can be seen in Figure 3.9. M&T Handling is an abbreviation for 'Materials and tools handling'. From the plot it can be seen that material and tool handling is the primary contributor to all accidents.



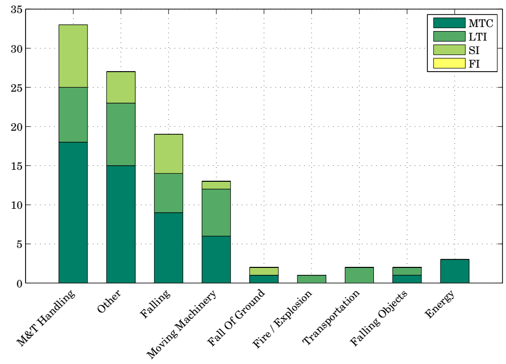
(a) Parent agency for total data set



(b) Parent agency for underground data



(c) Parent agency for engineering data



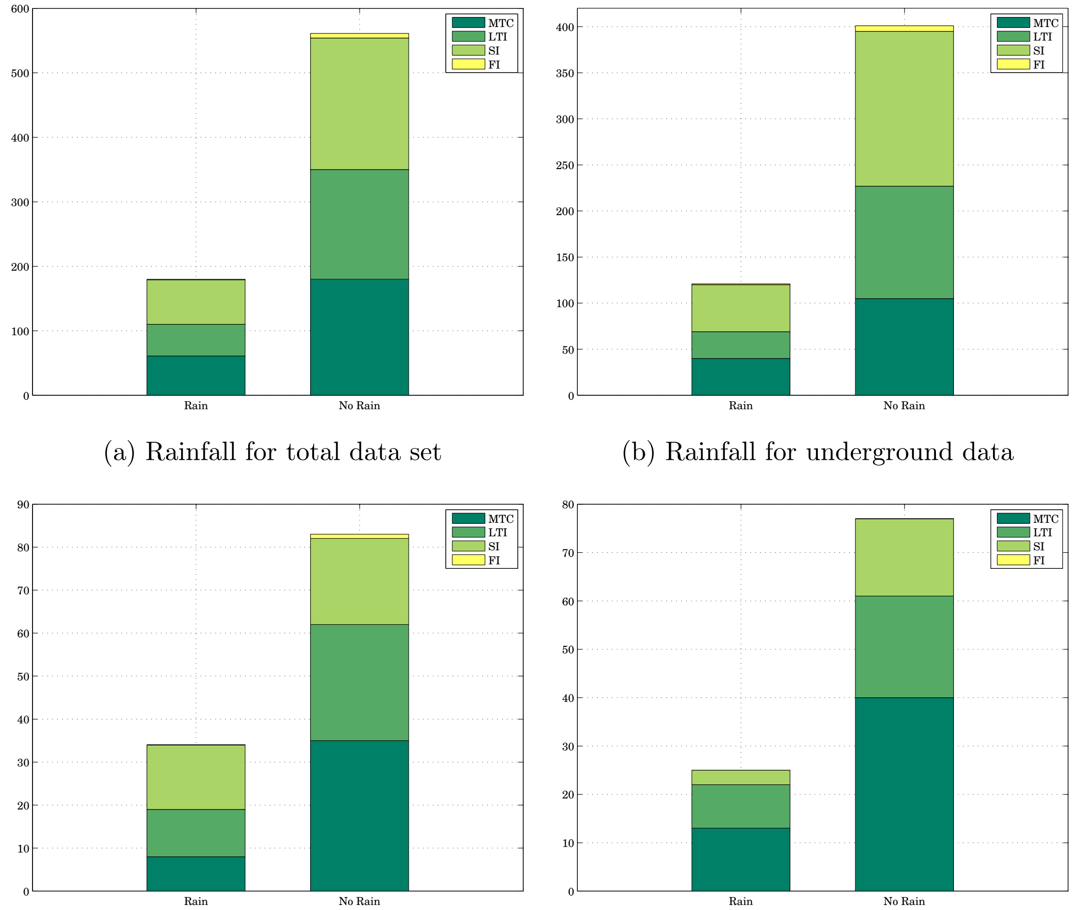
(d) Parent agency for the rest of the data

Figure 3.9: Parent agency analysis

However, in the underground sections, Fall Of Ground (FOG) is the next major contributor, yet for the engineering section, falling and moving machinery are the next major contributors, and for the rest of the sections, other, falling and moving machinery are the next major contributor to accidents. From this perspective, it appears that the engineering and other sections are similar, however, are distinguishable from the underground section.

3.4.4 Rain

Next, the rainfall was analysed, again on a total mine scale, and then in the three smaller data sets. This was to see if rain had any influence on the accidents occurring. Accidents were split up into if it was raining or not on the day that the accident occurred, as it was not recorded initially with the accident data. This was the best compromise that could be made to identify the influence of rain. The rain analysis can be seen in Figure 3.10. From these plots, it can be seen that the rainfall appears not to have any effect on whether or not an accident occurred, thus there is no obvious direct correlation between rain and an accident occurring. Intuitively, this is expected since the majority of operations in the platinum mining industry are underground or under a roof where rain will not influence the workers. In an open cast mine however, this



(a) Rainfall for total data set

(b) Rainfall for underground data

(c) Rainfall for engineering data

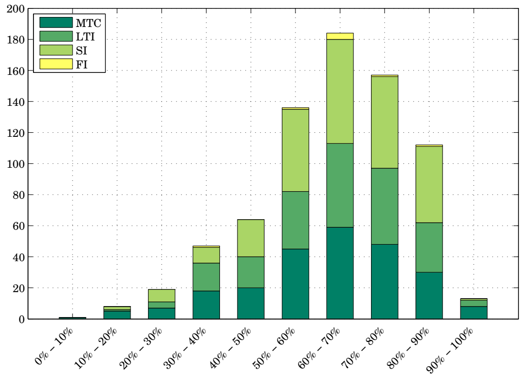
(d) Rainfall for the rest of the data

Figure 3.10: Rainfall analysis

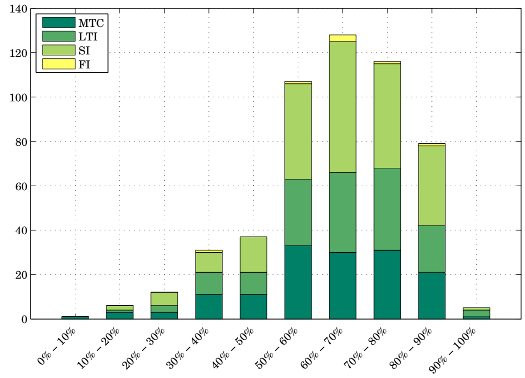
could be different.

3.4.5 Humidity

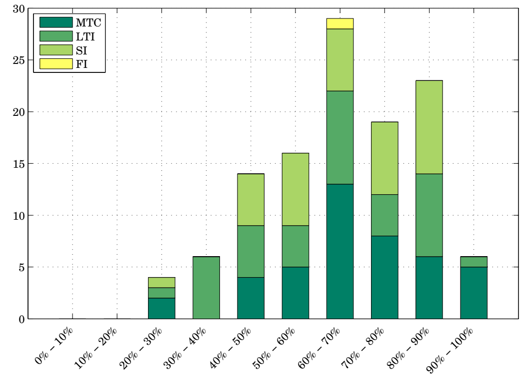
Humidity can range between zero and one hundred and was divided into ten equal segments for the analysis, which can be seen in Figure 3.11. From these plots, it can be seen that the humidity plays a similar role over all sections of the mine, and it appears that between 50% and 90% humidity the influence is much greater, with 60% to 70% humidity being the largest contributor to the risk of an accident occurring.



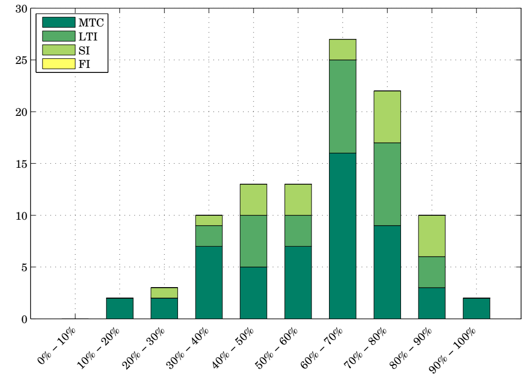
(a) Humidity for total data set



(b) Humidity for underground data



(c) Humidity for engineering data

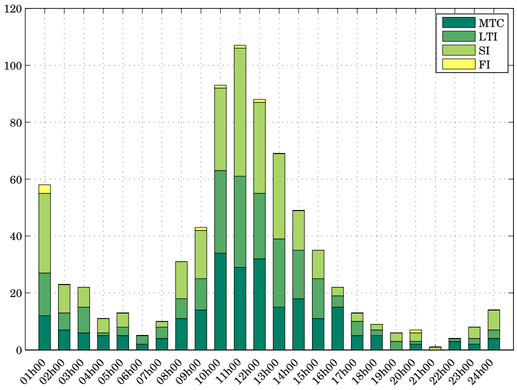


(d) Humidity for the rest of the data

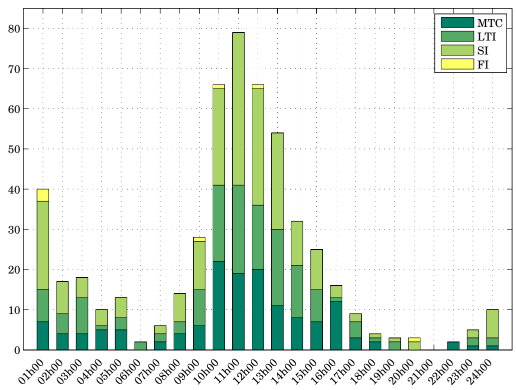
Figure 3.11: Humidity analysis

3.4.6 Time of day

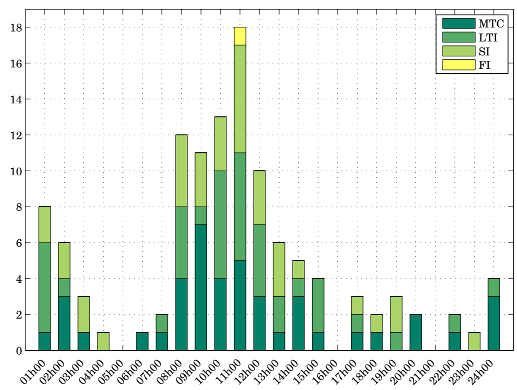
Each day was divided into 24 equal one hour groups and the accidents were analysed hourly. Figure 3.12 displays the results of this analysis. Earlier it was mentioned that time into shift was identified as an influential factor, however, no data was received with respect to the time into shift when each accident occurred. It is assumed that, since the data is separated into the three organisational units, the time into shift is incorporated in the time of day due to the fact that each organisational unit generally work similar shifts and as such, the time into shift that are of high risk will show up in the time of day plot for the individual organisational units. Nonetheless, from the plot it is assumed that there are two twelve hour shifts which are from 06h00 to 18h00 and from 18h00 to 06h00. From this figure, it can be seen that all the plots appear to have a very similar profile, which looks to follow a parabolic curve for the first half and an exponential function for the second half. This shows an overall high risk period between 24h00 and 01h00 and between 09h00 and 12h00 and low risk at the assumed shift changes.



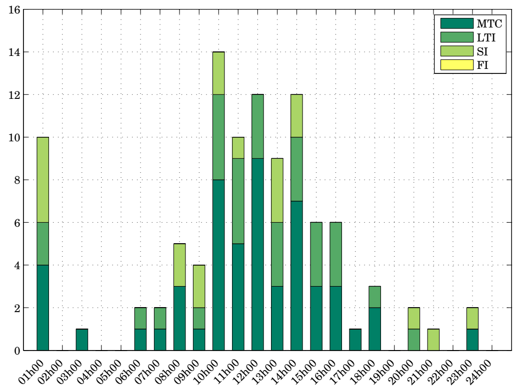
(a) Time of day for total data set



(b) Time of day for underground data



(c) Time of day for engineering data



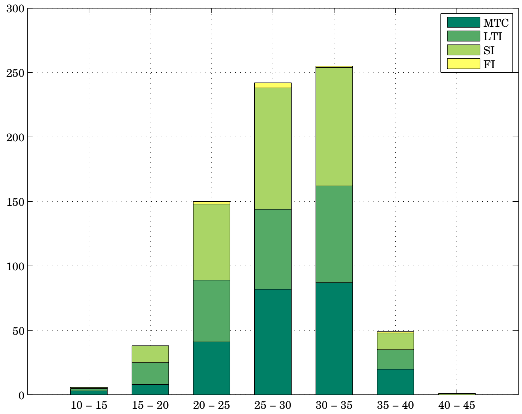
(d) Time of day for the rest of the data

Figure 3.12: Time of day analysis

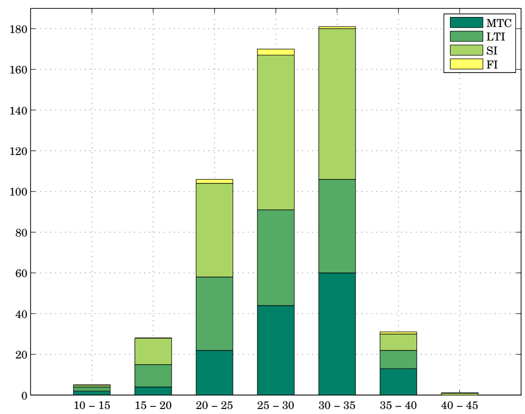
3.4.7 Temperatures

Next, the maximum temperature, minimum temperature and temperature difference was analysed. The temperature difference is the difference between the daily maximum and daily minimum temperatures. Unfortunately, only daily maximum and minimum temperatures were obtained, and not the exact temperature at the time of the accident. Thus instead of using an exact temperature at the time of the accident in the model, different variables will be used in the model for the day's maximum temperature, minimum temperature and the difference in the maximum and minimum temperatures. Figure 3.13 show the results from the analysis.

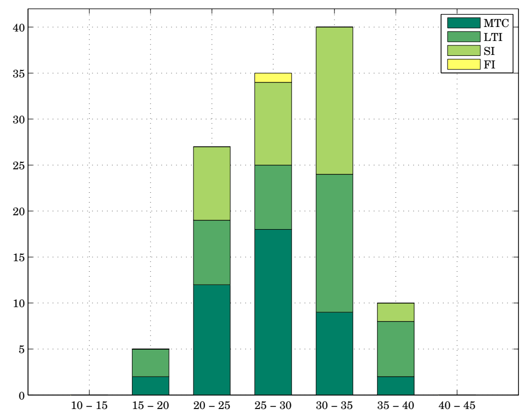
From all three of these plots, it appears that the individual organisational units follow the total data set, and all of the plots appear to follow a Poisson's distribution.



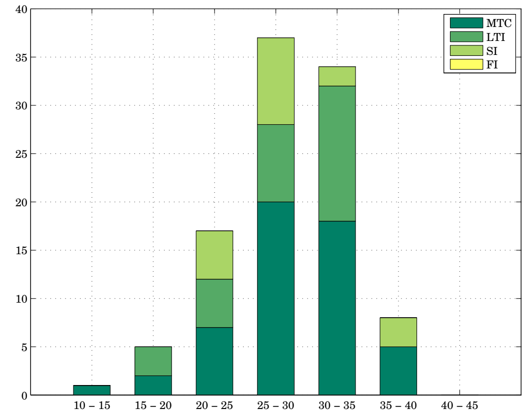
(a) Maximum temperature for total data set



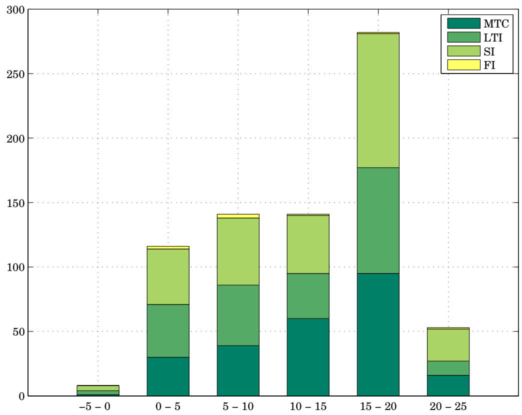
(b) Maximum temperature for underground data



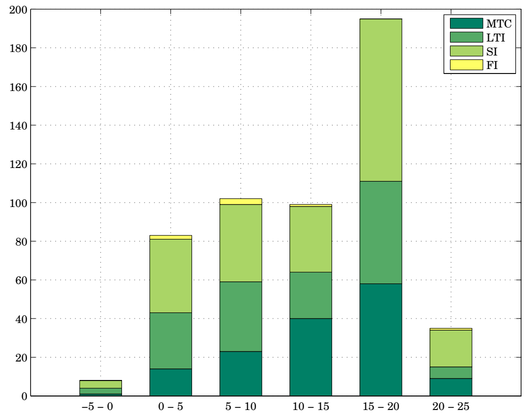
(c) Maximum temperature for engineering data



(d) Maximum temperature for the rest of the data

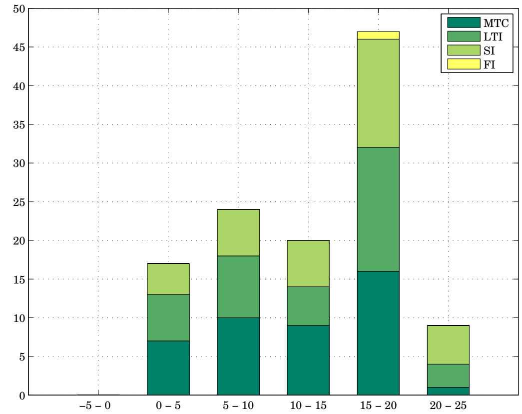


(e) Minimum temperature for total data set

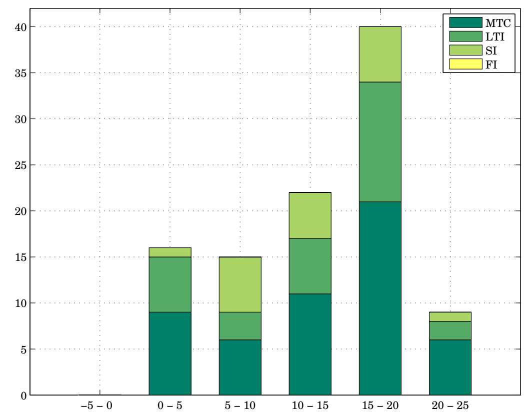


(f) Minimum temperature for underground data

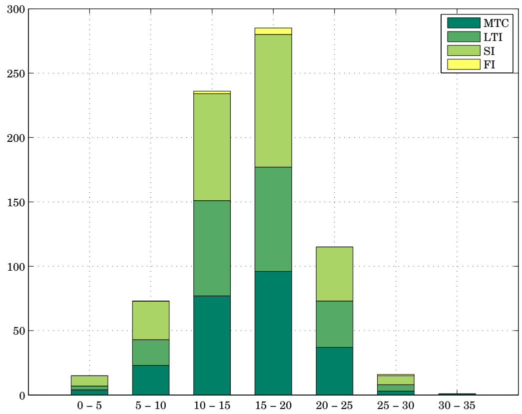
Figure 3.13: Temperature analysis



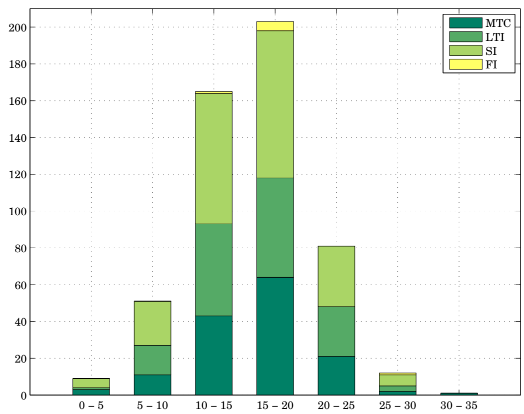
(g) Minimum temperature for engineering data



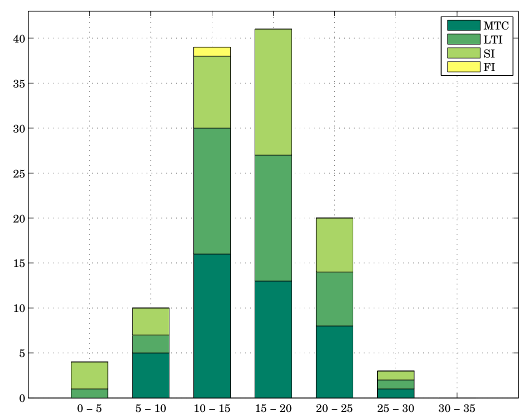
(h) Minimum temperature for the rest of the data



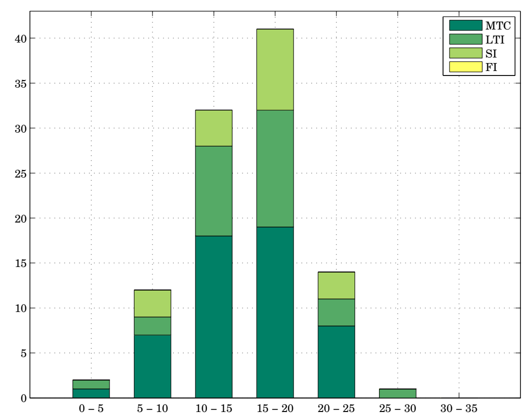
(i) Temperature difference for total data set



(j) Temperature difference for underground data



(k) Temperature difference for engineering data

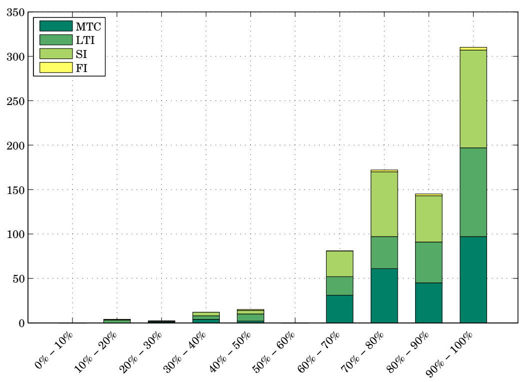


(l) Temperature difference for the rest of the data

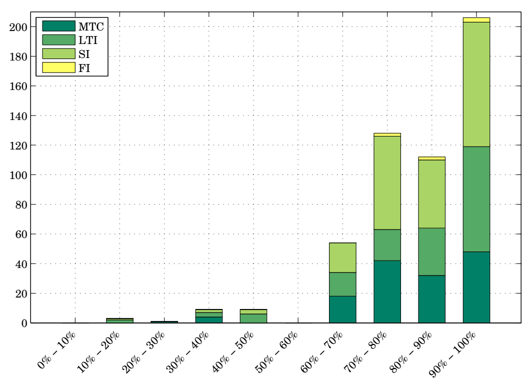
Temperature analysis continued

3.4.8 Production rate

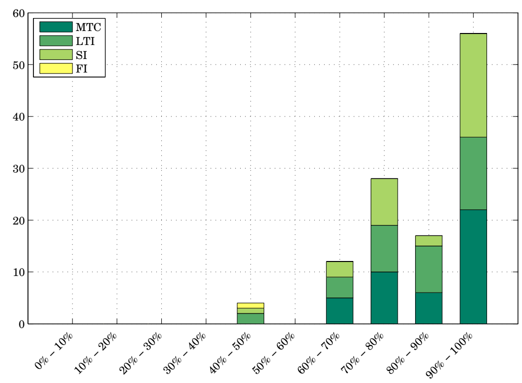
The production data received contained monthly totals for the tons broken/mined and the tons milled. For this analysis, these were added together and divided by the number of days in the month, after which this value was normalised to a value of between zero and one which reflected the production percentage relative to the maximum daily tonnage. Figure 3.14 shows the results of this analysis.



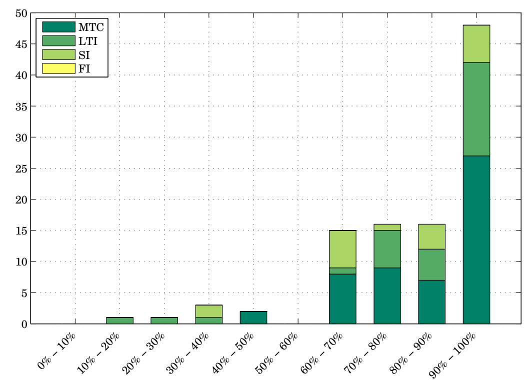
(a) Production rate for total data set



(b) Production rate for underground data



(c) Production rate for engineering data



(d) Production rate for the rest of the data

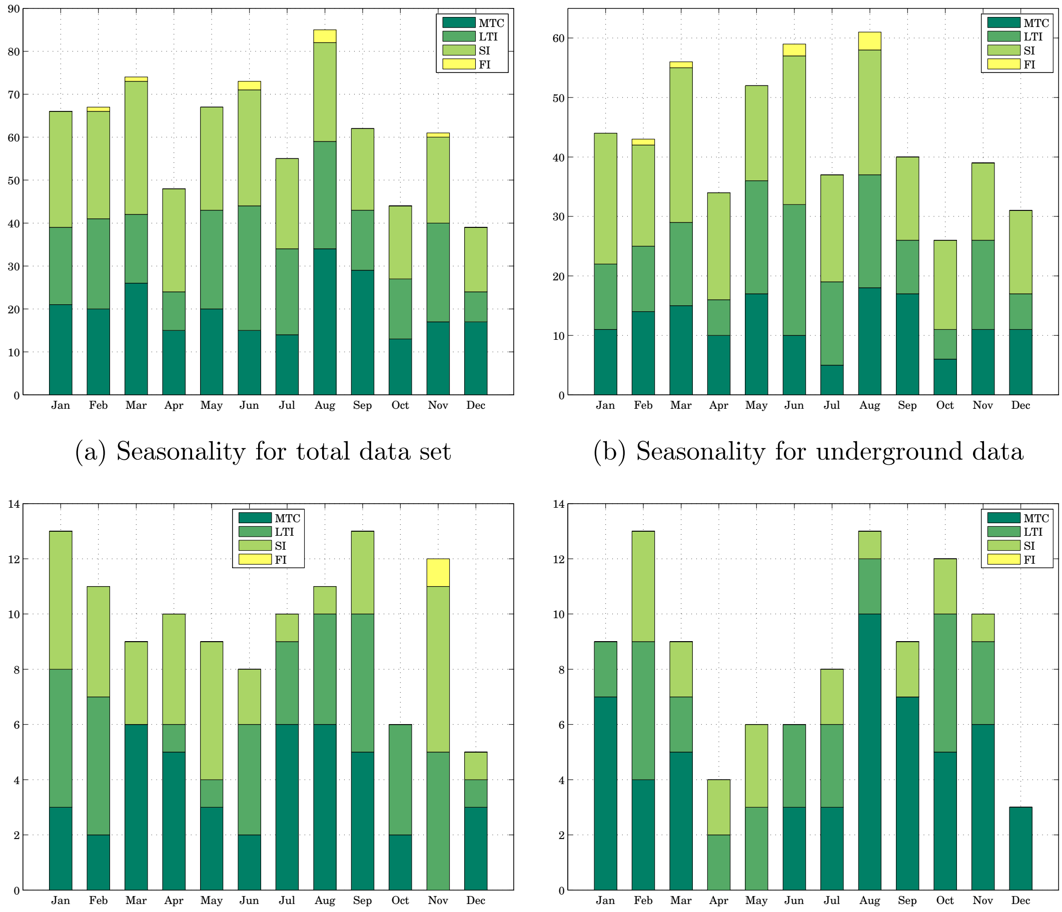
Figure 3.14: Production rate analysis

As was assumed, this plot shows an exponential distribution, with the larger production rate resulting in more accidents and the lower the production rate resulting in a lower accident rate.

3.4.9 Seasonality

Lastly, the months were analysed to identify any pattern due to seasonality. Figure 3.15 presents the results.

This plot shows that the accident data had a fairly constant spread over each month and thus showed no significant seasonality affect, because there was no recognisable trend or pattern throughout the year. However, there was a strike over the period of October 2012 to December 2012 and thus that would account for the drop in accidents over that period.



(a) Seasonality for total data set

(b) Seasonality for underground data

(c) Seasonality for engineering data

(d) Seasonality for the rest of the data

Figure 3.15: Seasonality analysis

3.5 Input Attribute Normalised Continuous Approximations

From the section above it was identified that there was no significant difference between the total data distributions and each of the three analysed organisational units (underground, engineering and other) distributions for each attribute analysed. As such, normalised continuous approximations were created for the input attributes based on the total distributions. This was done in order to normalise the input data, as well as for ease of programming. Of the attributes analysed above, the parent agency and seasonality is omitted since no significant trends or deductions can be made from them. Additionally, the rain attribute is also omitted due to the fact that it would be programmed as a one for rain, and a zero for no rain, and thus no normailisation is required for the rain. All of the normalised continuous approximations are plotted along with their associated distributions to see the resemblance between the two. In Figure 3.16 to Figure 3.21 of the normalised continuous approximations, the left hand y-axis represents the scale for the distribution of accidents, and the right hand y-axis represents the scale for the normalised approximation.

Firstly, a normalised continuous approximation plot was created for the humidity distribution. By visual inspection, the best fit curve to this distribution was found to be a scaled 6^{th} order polynomial which can be seen in Figure 3.16. Next, the best fit curve for the time of day distribution was found to be a 10^{th} order polynomial which can be seen in Figure 3.17. Next, the best fit curve for the maximum temperature distribution was found to be a 5^{th} order polynomial which can be seen in Figure 3.18. Next, the best fit curve for the minimum temperature distribution was found to be a 4^{th} order polynomial which can be seen in Figure 3.19. Next, the best fit curve for the temperature difference distribution was found to be a 6^{th} order polynomial which can be seen in Figure 3.20. Lastly, the best fit curve for the production rate distribution was found to be an exponential distribution which can be seen in Figure 3.21.

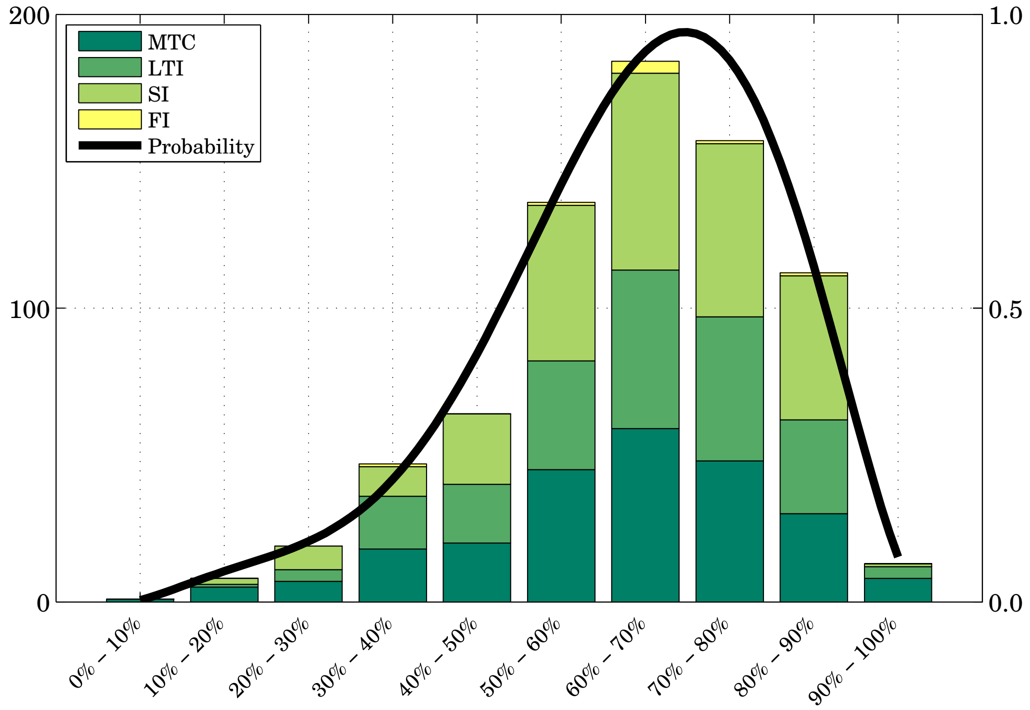


Figure 3.16: Normalised continuous approximation for humidity

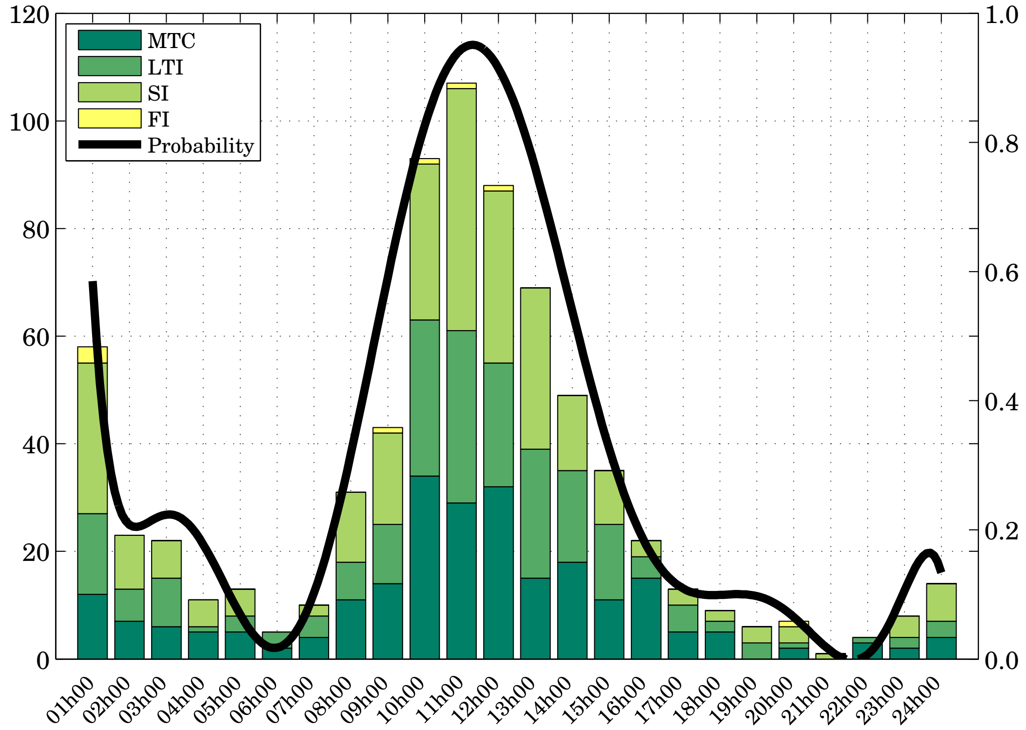


Figure 3.17: Normalised continuous approximation for time of day

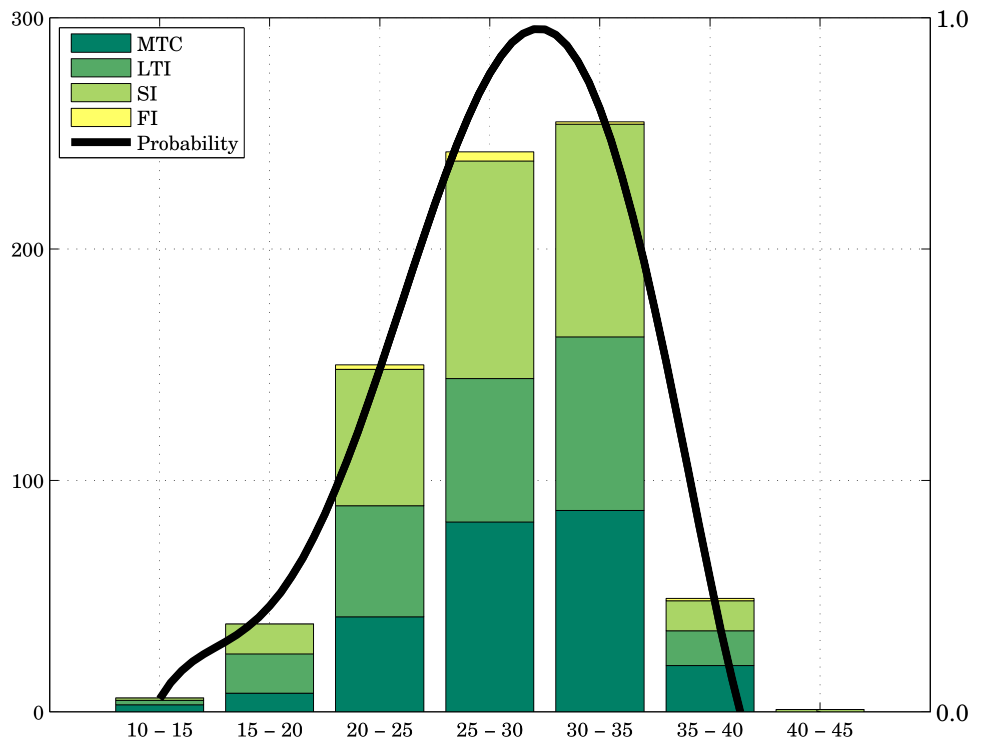


Figure 3.18: Normalised continuous approximation for maximum temperature

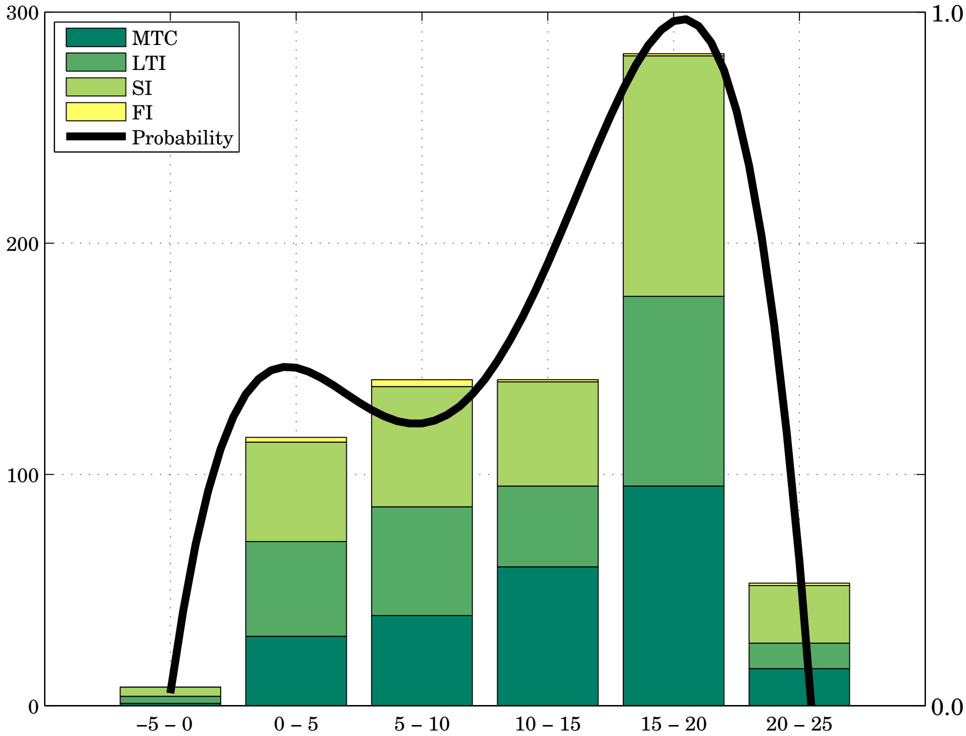


Figure 3.19: Normalised continuous approximation for minimum temperature

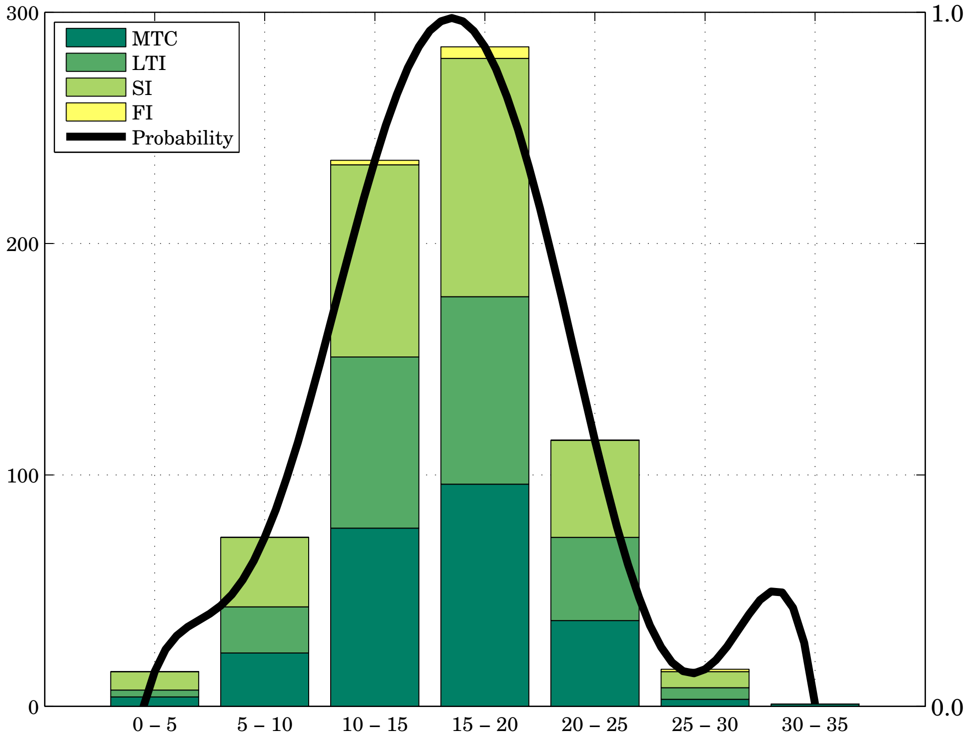


Figure 3.20: Normalised continuous approximation for temperature difference

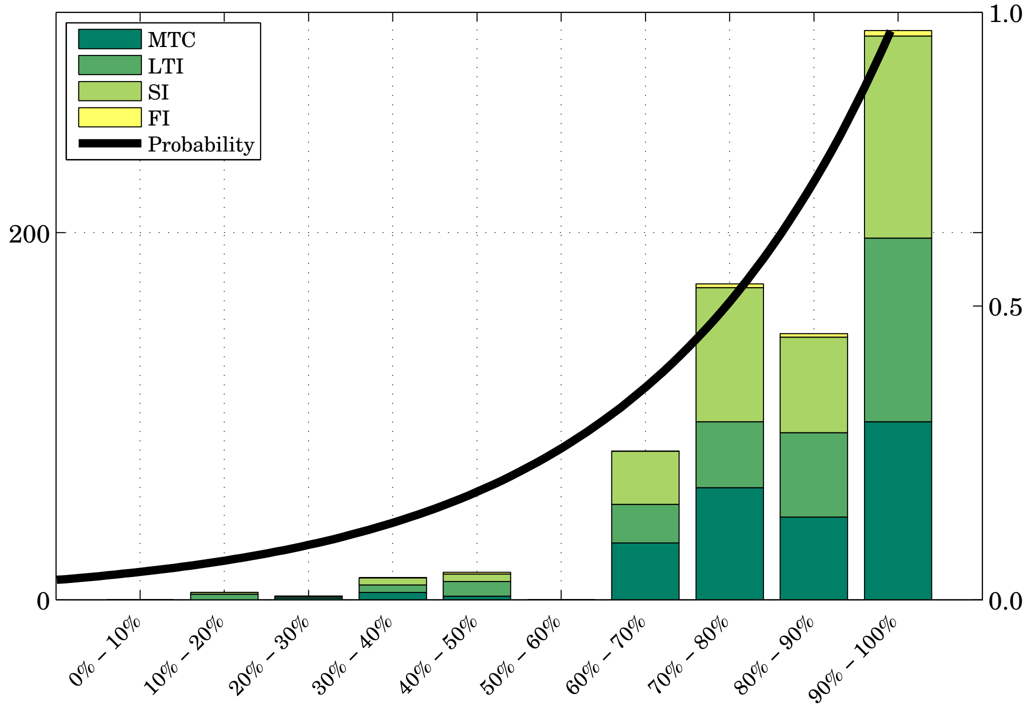


Figure 3.21: Normalised continuous approximation for production rate

3.6 Data Setup

After the data was split into three major sections, namely, underground, engineering and other, it was chosen to train the model with 80% of the data and validate it with the remaining 20%. This corresponded to training with the first four years (2009 – 2012), and validating with the last year (2013). However, with the improvement of safety initiatives over the years as well as organisational restructuring, this approach to the model did not yield adequate results, thus an alternative method was identified. This alternative method was to create a network for each year (2009 – 2012), and then validate each network with the subsequent year (2010 – 2013), thus creating four separate networks for each of the three sections. The various networks discussed above refer all to the same model discussed, however, with different network weights associated to each model.

Next, 25 converse arguments were created to be used in the training of the model in order to help train the model. They were necessary due to the fact that if there are no examples in the network training that identify when there is no accident, then the network would always generalise that for any inputs that the output would be an accident.

The model was used to identify patterns between the influencing factors for each accident (and converse arguments) and then generalise the pattern, to be used to identify the continuous risk. Due to this pattern recognition approach, the network makes use of a binary output classification system also known as a *1-of-n* output structure. The *1-of-n* output structure for this model operates as follows, there are ten outputs which correspond to the output in units of 10% (i.e. the first output refers to any output between 0% and 10%, the second output refers to any output between 10% and 20%, and so on). For example, if the first converse argument is 35% risk, then for that training entry, all the cells are zero, except for the fourth cell which is populated with a one. Therefore, the entire output matrix is populated with ones and zeros, and each example can only have a single one in it. An example of this can be seen in Table 3.5. With this system, the outputs for the converse arguments were ranged between the first seven columns, putting more emphasis on the lower risks because the accidents put the emphasis on the higher risks. The accidents were defined as follows, the output for a FI and SI was assumed to be between 90% and 100%, for a LTI was assumed to be between 80% and 90%, and for a MTC was assumed to be between 70% and 80%. This was done so that each category from 0% to 100% had data points to train.

Next, all the data was manipulated according to the normalised continuous approximations discussed earlier and the outputs were manipulated as mentioned above. Although no time into shift data was received, it was assumed that there are two shifts, from $6h00$ to $18h00$ and $18h00$ to $6h00$. Table 3.5 is a sample of the training inputs and outputs to the network.

Table 3.5 shows how all the accident data and converse arguments were manipulated for training the networks. Continuous data for the five years $(2009 - 2013)$ was also manipulated similarly, however without any corresponding output values. The continuous data was broken down into two hour segments for the entire five years, this was so that the time of day and time into shift have influence on the network. Then for the temperatures, humidity and rain which was only recorded daily, the same values were used consecutively over the twelve 2-hour entries, thus assuming the entire day had the same conditions, although this is not completely accurate, since the humidity would change throughout the day, or the rain may only fall for an hour or two of the entire day, this was the best generalisation that could be made with the available data. Furthermore, the production figures received were the monthly figures, not daily or hourly, thus every entry for the same month was assumed to be the same production value, again this is not completely accurate, however, it was the best assumption that could be made with the data available.

After the data has been setup as described above, the model can be trained and validated, which is discussed in the next chapter.

3.7 Chapter 3 Concluding Remarks

In conclusion, this chapter described the model created for this study as well as the mathematics used in ANN more closely. This was followed by an example for clarity on the mathematics. After which, the data obtained was analysed and ultimately, normalised continuous approximations for the input attributes

Table 3.5: Manipulated accident data

	Accident			Non-Accident		
No.	1	2	3	1	2	3
Risks						
Time of Day	0.670	0.102	0.287	0.820	0.680	0.640
Time into Shift	0.353	0.135	0.418	0.030	0.210	0.490
Temp - max	0.984	0.984	0.834	0.770	0.890	0.940
Temp - min	0.897	0.897	0.968	0.670	0.950	0.710
Temp - diff	0.536	0.432	0.199	0.730	0.600	0.900
Humidity	0.820	0.902	0.939	0.570	0.610	0.920
Rain	1.00	1.00	0.00	1.00	1.00	1.00
Production	0.761	0.761	0.761	0.890	0.930	0.860
Output	SI	SI	MTC	5%	24%	56%
Output1 (0% - 10%)	0	0	0	1	0	0
Output2 (10% - 20%)	0	0	0	0	0	0
Output3 (20% - 30%)	0	0	0	0	1	0
Output4 (30% - 40%)	0	0	0	0	0	0
Output5 (40% - 50%)	0	0	0	0	0	0
Output6 (50% - 60%)	0	0	0	0	0	1
Output7 (60% - 70%)	0	0	0	0	0	0
Output8 (70% - 80%)	0	0	1	0	0	0
Output9 (80% - 90%)	0	0	0	0	0	0
Output10 (90% - 100%)	1	1	0	0	0	0

were created from this data for all the input attributes into the model. Lastly, the data setup for use in the model was explained.

Chapter 4

Training And Validation Of The Model

4.1 Introduction

Training and validation of the model designed is necessary to guarantee the model functions as designed as well as to ensure the rigidity of the model. The training of the model is accomplished using Matlab's pattern recognition neural network tool with the data as processed in the previous chapter and the validation of the model takes the form of a case study by observing and comparing the model risk outputs with the actual accidents. The model design can be broken up into three parts which are repeated for each year (2009 – 2012), the three sections are underground, engineering and other. The other section is a grouping of the following five sections, smelter services, smelter, services, concentrators and surface mining. This chapter starts by covering the training of the model, followed by the validation of the model, then the actual model for the various sections and years are created, a sensitivity analysis of the input variables is performed, the various networks are compared and discussed and lastly, the intended use of the model is discussed.

4.2 Training of the Model

As was identified in the former chapter, the data was divided into three major sections, namely, underground, engineering and other. Initially, it was chosen to train the model with 80% of the data and validate it with the remaining 20% which corresponded to training with the first four years (2009 – 2012) and validating with the last year (2013). However, with the improvement of safety initiatives over the years as well as organisational restructuring, this approach to the model did not yield adequate results, thus an alternative method was identified. This alternative method was to create a network for each year (2009 – 2012) and then validate each network with the succeeding year (2010 – 2013). The various networks discussed above refer all to the same model discussed in the preceding chapter, however, with different network weights associated to each network. Furthermore, 25 converse arguments were created to be used in the training of the model in order to assist training the model. Since if there were no converse arguments, the model would generalise that for any inputs, the output would result in an accident. The converse arguments used conditions when accidents did not occur.

A two-layer feed-forward neural network, with sigmoid hidden and output activation functions was the network used in the model. This type of network can classify vectors well, given sufficient nodes in its hidden layer. For each of the three sections, for each year, a network was trained and validated. For each network, the manipulated input values associated to the accidents and the converse arguments as well as the target outputs are loaded into the neural network pattern recognition tool in Matlab. Then on average, a data split of 70% data for network training, 25% data for network validation and 5% data for network testing is selected. These values were the best values found from trial and error. The network training data is used to train the network and adjust the network weights according to its error. The network validation data is used to measure the networks generalisation and to stop the training when generalisation stops improving. Lastly, the network testing data has no effect on the training and it provides an independent measure of network performance during and after training. Next, the number of hidden nodes are set, from the previous chapter it was stated that two thirds of the sum of the number of inputs and outputs is an adequate number of hidden nodes to use, this corresponds to twelve hidden nodes, since there are eight inputs and ten outputs. Each network used start with twelve hidden nodes, however, after many iterations some models ended up requiring more hidden nodes.

Next, the network was trained numerous times and the best network was saved. Note must be taken that training multiple times would generate different results due to different initial conditions and sampling, furthermore, note must be taken that the lowest training error is not necessarily the best solution, as the network will not always generalise as well as a network with a slightly higher training error. A method can be to train with half the data and validate with the other half of the data until a suitable network approximates the entire data set and this can be used for the model. When a suitable Mean Square Error (MSE) is reached the retraining can stop. The MSE is the average squared difference between outputs and targets, intuitively lower values are better and zero implies no error. The total percentage error found in the confusion matrix indicates the fraction of samples misclassified, intuitively a value of zero implies no misclassification.

At this point a confusion matrix can be plotted to check where the misclassifications occurred in order to identify if they are of the accidents or converse arguments as well as if the misclassification is minor (such as a Serious Injury (SI) being classified as a Lost Time Injury (LTI)) or major (such as a SI being misclassified as a 10% risk). The confusion matrix has the network output on the y-axis and the target output on the x-axis, thus the main diagonal (from the top left to bottom right) indicates correct classification and the rest of the blocks indicate misclassification, however, the blocks close to the main diagonal are minor misclassifications and the further away from the diagonal the more large the misclassification is. All misclassifications below the main diagonal are where the network predicts higher outputs than the targets and above the main diagonal the network predicts lower output values than the targets.

After the errors are suitable and a model is selected and the confusion matrix is satisfactory, then the network can be validated by running continuous data through it and comparing the output with the actual accidents which is discussed in the next section.

4.3 Validation of the Model

As discussed in the section above, the model is validated by testing each network with data from the year it was trained with and with data from the subsequent year, which is plotted along with the actual accidents that occurred in the corresponding year. Making use of the best chosen network for each year, the network is run with continuous data from its own year and the next year which was manipulated as presented in the former chapter. The output of the model returns for each time step a vector of ten values which corresponds to the ten outputs, and every value in each vector relates to the correlation of each output, thus if there is a one in the tenth output, this implies the model is certain that the output is a SI, however, if that value was 0.1 then the network is not certain that it is a SI. Thus which ever output has the maximum correlation it is assumed to be the output value. For example in Table 4.1, the maximum value is 0.9882 which corresponds to the output risk being between $60\% - 70\%$. However, if the maximum value and second highest value is close together then no clear distinction can be made between the two categories. Thus for the purpose of this model, if the difference between the maximum value and second highest value is more than or equal to 0.2 then the maximum value is used, on the other hand, if the difference between the maximum value and second highest value is less than 0.2 then the average output between those two outputs is used.

Next, the output is averaged to a daily risk value. Then the daily risk is plotted along with the actual accidents and this is performed for the current year of the model as well as the subsequent year. Then these continuous risk profiles can visually be compared with the actual accidents to validate the model. Ideally, the risk should remain low and only peak when an accident occurs, however, due to the random nature of accidents and so few input influential factors and the generalisations made, the risk may peak when no accidents occur, or the risks may be low when an accident occurs. However, it is attempted to minimise the modelling error of high risks and no accidents and vice versa. The plots all have colour bands in the background to differentiate the various risk levels, these levels were set as high risk is anything above 90% which is red, moderate risk is anything between 80% and 90% which is yellow and acceptable risk is anything below 80% which is green.

Table 4.1: Example network output for a single 2 hour time slot

Attribute	Correlation
0% - 10%	0.0460
10% - 20%	0.0003
20% - 30%	0.0005
30% - 40%	0.0048
40% - 50%	0.0142
50% - 60%	0.0039
60% - 70%	0.9882
70% - 80%	0.0007
80% - 90%	0.0026
90% - 100%	0.0145

The next section presents the results of the training and validation for the underground, engineering and other sections for the years 2009 to 2012, which is followed by a sensitivity analysis and a discussion of the results.

4.4 Results and Discussion

There are three subsections which the results are broken up into. They are the underground section, engineering section and the other sections. For each of these subsections a network was created for the years 2009, 2010, 2011 and 2012. Then each of these networks where tested with the data from the year it was trained with, as well as the data from the following year. Next, the underground section's networks are trained and validated.

4.4.1 Underground

The underground section contributed 522 accidents to the total (741) of non-duplicated accidents, this was comprised of 128 in 2009, 98 in 2010, 112 in 2011, 91 in 2012 and 93 in 2013. With such a high number of accidents occurring in the underground section continuously, it can be seen that the underground section is continuously at a high risk of an accident occurring. These accidents along with the converse arguments were used in training the networks below. The accident numbers over the five years drop from 2009 to 2010 and then from 2010 to 2013 the accident numbers stayed fairly constant, besides for a small increase in 2011. Next, the four underground networks are created.

4.4.1.1 2009 underground network

In 2009 the underground section had 128 accidents which equates to roughly 2.5 accidents every week. Knowing that on average an accident occurred every three days, it is assumed that the networks calculated risk will almost always stay above 80% risk. The 2009 underground network created made use of the training setup of 70% data for network training, 25% data for network validation and 5% data for network testing along with twelve hidden nodes which resulted in the following training errors,

Table 4.2: MSE for 2009 underground network

	MSE
Training	0.0276
Validation	0.0416
Testing	0.0317
Total	0.0313

As can be seen from the errors, the 2009 network had an average error in the training, validation and testing steps, which resulted in an acceptable total for the network. Next the confusion matrix is plotted in Figure 4.1 to identify where the misclassifications occurred. From the confusion matrix it is seen that the majority of the data is correctly classified (along the main diagonal) and the majority of the misclassifications are close to the main diagonal, implying that they are close to their actual value. There are very few major misclassification and they predominantly occurred as low target values being classified as high output values. Since the majority of the misclassifications occur below the main diagonal, it is assumed the network will be biased more towards higher outputs. 14.1% of the classifications occur below the main diagonal and 8.7% of the classifications occur above the main diagonal, thus there is a bias of 5.4% towards a higher output. This resulted in a classification accuracy of 77.8% or error of 22.2%.

Next, Figure 4.2 shows the calculated continuous risk profile along with the actual accidents that occurred in 2009, this was used in the training described above. From this plot it can be seen that the continuous risk varies between 65% and 100%, however, the majority of the risk lies above 80%. The actual accidents that occurred in 2009 are plotted on the continuous risk line and this shows a few outliers that occur at a risk below 80%. Unfortunately due to the number of accidents occurring in the underground section which portrays the high danger in the underground section, the risk stays above 80% for the majority of the time and thus not much use can be gained from the underground networks.

Output Class \ Target Class	1	2	3	4	5	6	7	8	9	10	
1	2.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100% 0.0%
2	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	NaN% NaN%
3	0.0%	0.0%	2.6%	0.0%	0.7%	0.0%	0.0%	0.0%	0.0%	0.0%	80.0% 20.0%
4	0.0%	0.0%	0.0%	2.0%	0.7%	0.0%	0.7%	0.7%	0.0%	0.0%	50.0% 50.0%
5	0.0%	0.7%	0.0%	0.0%	1.3%	0.0%	0.0%	0.0%	0.0%	0.0%	66.7% 33.3%
6	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	NaN% NaN%
7	0.0%	0.7%	0.0%	0.0%	0.0%	0.0%	0.7%	0.0%	0.0%	0.0%	50.0% 50.0%
8	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	15.7%	1.3%	2.0%	82.8% 17.2%
9	0.0%	0.7%	0.0%	0.7%	0.0%	0.7%	0.0%	2.0%	17.6%	2.6%	73.0% 27.0%
10	0.7%	0.7%	0.0%	0.0%	0.0%	1.3%	0.0%	3.3%	2.6%	35.9%	80.9% 19.1%
	75.0% 25.0%	0.0% 100%	100% 0.0%	75.0% 25.0%	50.0% 50.0%	0.0% 100%	50.0% 50.0%	72.7% 27.3%	81.8% 18.2%	88.7% 11.3%	**77.8% 22.2%**

Figure 4.1: Confusion matrix for 2009 underground network

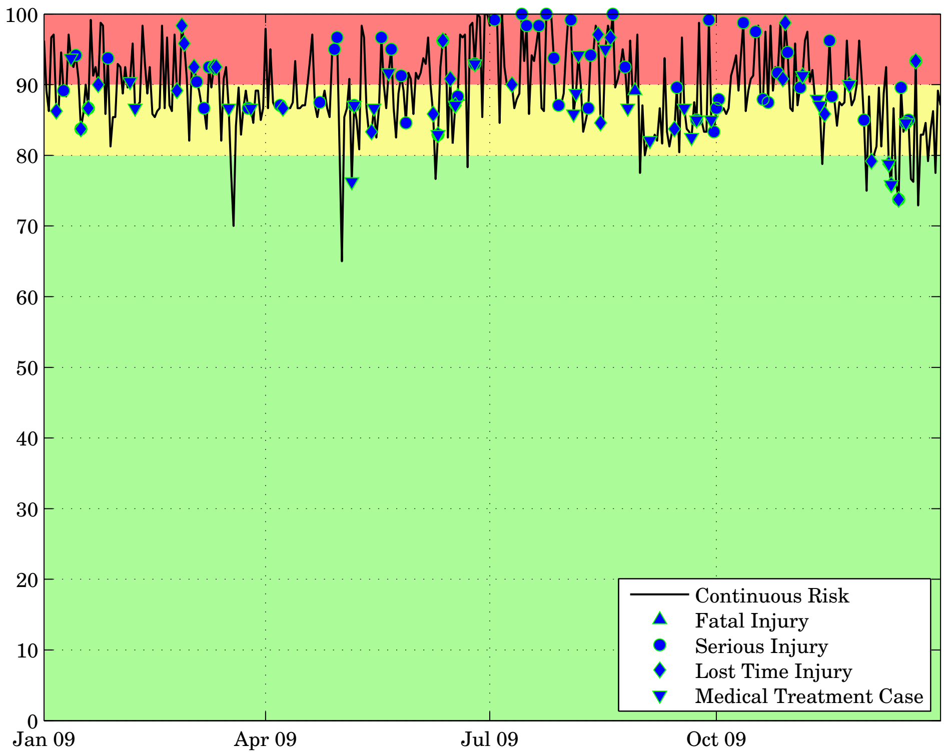


Figure 4.2: Continuous risk for 2009 underground section

Next, this network was used to estimate the risk in the next year (2010) which was plotted along with the actual accidents in 2010 and this can be seen in Figure 4.3. This plot shows again that the continuous risk varies between 71% and 100%, however, the majority if the risk lies above 80%. However, this time all the accidents occur above 80% risk.

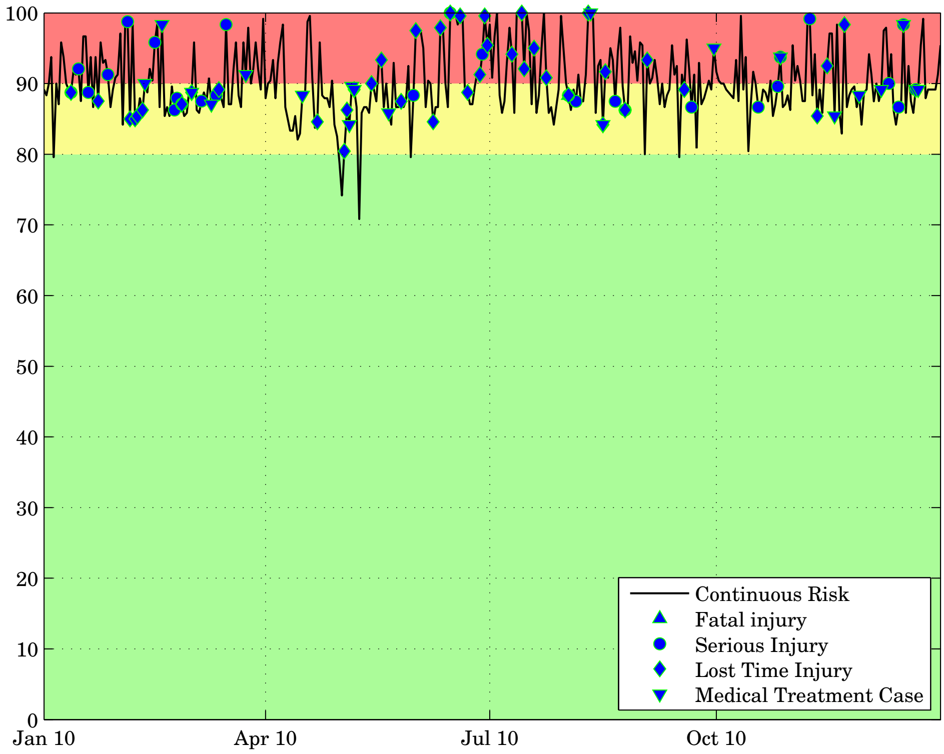


Figure 4.3: Predicted continuous risk for 2010 underground section

4.4.1.2 2010 underground network

In 2010 the underground section had 98 accidents which equates to roughly 1.9 accidents every week. Knowing that on average an accident occurred every four days, it is assumed that the networks calculated risk will almost always stay above 80% risk. As with the majority of networks, the 2010 underground network created made use of the training setup of 70% data for network training, 25% data for network validation and 5% data for network testing along with twelve hidden nodes which resulted in the training errors seen in Table 4.3.

As can be seen from the errors, the network had a low training error and the validation error was acceptable and despite the higher testing error, this resulted in an acceptable error for the total network. Next, Figure 4.4 shows the confusion matrix associated to this network. The confusion matrix showed very few misclassifications and of the misclassifications, the majority were close to the main diagonal which is better than them further away from the

Table 4.3: MSE for 2010 underground network

	MSE
Training	0.0184
Validation	0.0333
Testing	0.0746
Total	0.0249

main diagonal. In the network 12.1% of the classifications occurred below the main diagonal and 5.6% occurred above the main diagonal, again showing a bias towards higher outputs but only of 6.5% this time. This resulted in the trained models accuracy being 82.1%, or having an error of 17.9%.

Output Class \ Target Class	1	2	3	4	5	6	7	8	9	10	
1	2.4%	0.8%	1.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	50.0% 50.0%
2	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	NaN% NaN%
3	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	NaN% NaN%
4	0.0%	0.0%	0.8%	3.3%	0.8%	0.0%	0.0%	0.0%	0.0%	0.0%	66.7% 33.3%
5	0.8%	0.8%	0.8%	0.0%	2.4%	0.0%	0.0%	0.0%	0.0%	0.0%	50.0% 50.0%
6	0.0%	0.8%	0.0%	0.0%	0.0%	2.4%	0.8%	0.0%	0.0%	0.0%	60.0% 40.0%
7	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	NaN% NaN%
8	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.8%	15.4%	0.0%	0.8%	90.5% 9.5%
9	0.0%	0.8%	0.0%	0.0%	0.0%	0.0%	0.0%	0.8%	31.7%	0.8%	92.9% 7.1%
10	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	2.4%	3.3%	24.4%	81.1% 18.9%
	75.0% 25.0%	0.0% 100%	0.0% 100%	100% 0.0%	75.0% 25.0%	100% 0.0%	0.0% 100%	82.6% 17.4%	90.7% 9.3%	94% 6.3%	**82.1% 17.9%**

Figure 4.4: Confusion matrix for 2010 underground network

Figure 4.5 presents the continuous risk profile along with the actual accidents that occurred in 2010. This figure shows that the continuous risk varies between 61% and 100%, with the majority of the risk varying between 80% and 100%. There are two outlying accidents which occur at roughly 74% and 79%, the rest of the accidents occur above 80%. Again, the risk stays above

80% as was assumed, however, all this infers is that the underground section is very dangerous and at constant risk of an accident.

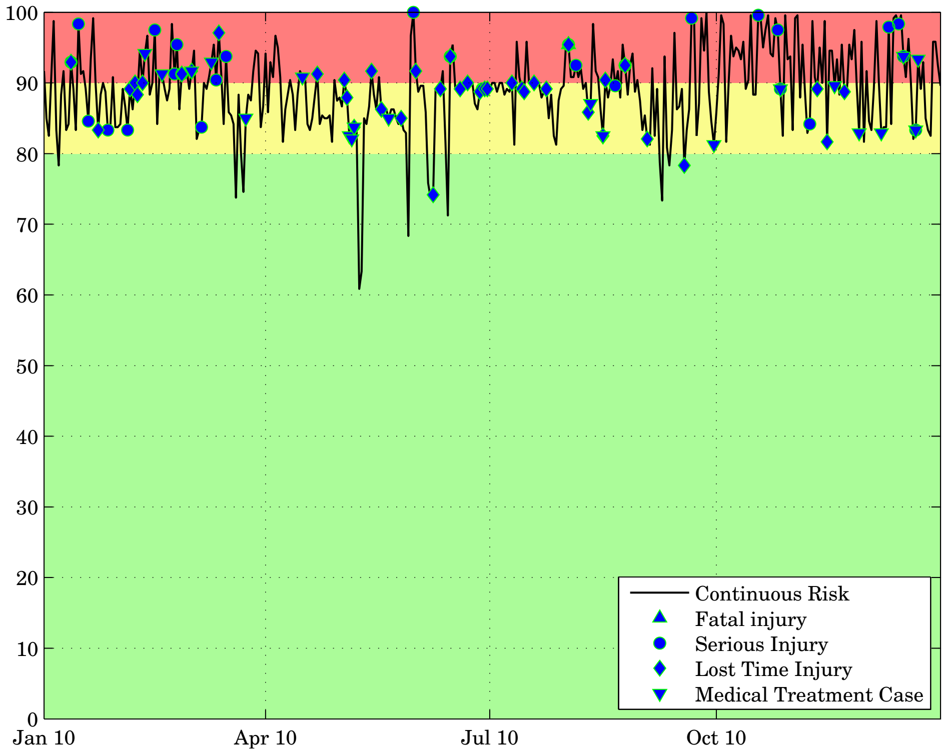


Figure 4.5: Continuous risk for 2010 underground section

Next, this network was used to estimate the risk in the next year (2011) which was plotted along with the actual accidents in 2011 and this can be seen in Figure 4.6. This plot ranges between 54% and 98%, with the majority of the risk staying between 80% and 90% and all of the accidents occurring above 80% risk.

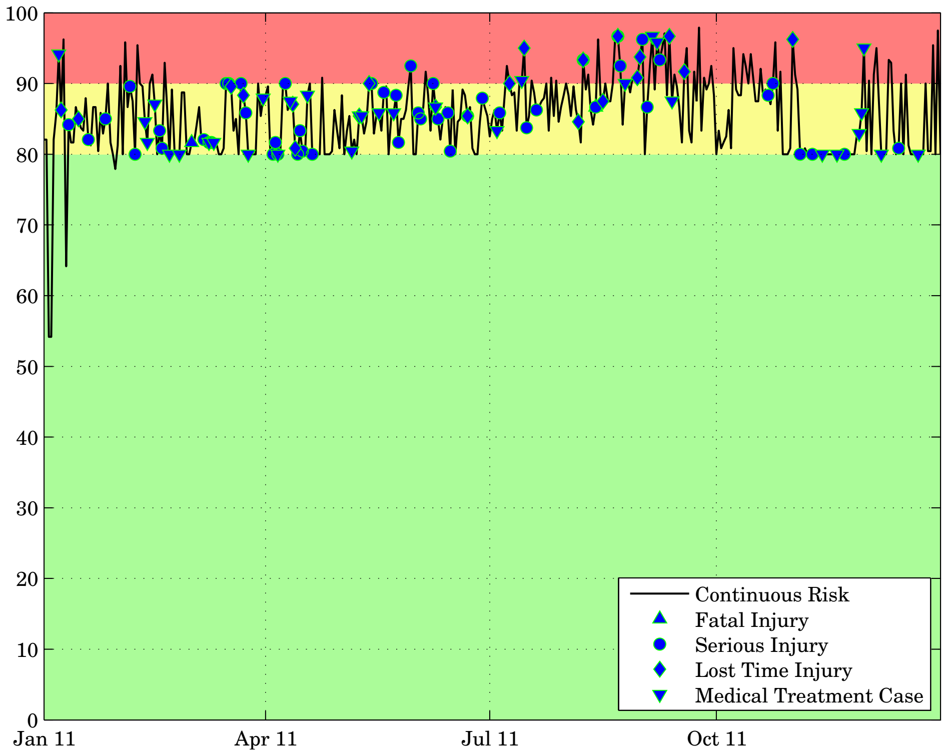


Figure 4.6: Predicted continuous risk for 2011 underground section

4.4.1.3 2011 underground network

In 2011 the underground section had 112 accidents which equates to roughly 2.2 accidents every week. Knowing that on average an accident occurred every three days, it is assumed that the networks calculated risk will almost always stay above 80% risk. Again, the 2011 underground network created made use of the training setup of 70% data for training, 25% data for validation and 5% data for testing along with twelve hidden nodes which resulted in the following training errors,

Table 4.4: MSE for 2011 underground network

	MSE
Training	0.0309
Validation	0.0438
Testing	0.0635
Total	0.0358

As can be seen, the network had an acceptable training and validation error and despite the higher testing error, the total error was low enough, which resulted in a suitable network. Then the confusion matrix for this network was plotted in Figure 4.7 and it shows that the majority of the misclassifications occur close to the main diagonal and as such are not a problem. Furthermore, 12.3% of the classifications occurred below the main diagonal and 12.3% of the classifications occurred above the main diagonal, thus there is no bias towards lower or higher output values. This resulted in a training classification accuracy of 75.2% or an error of 24.8%.

Output Class \ Target Class	1	2	3	4	5	6	7	8	9	10	
1	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	NaN% NaN%
2	0.0%	0.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100% 0.0%
3	0.7%	0.0%	2.2%	0.0%	0.7%	0.7%	0.7%	0.0%	0.0%	0.0%	42.9% 57.1%
4	0.0%	0.0%	0.0%	2.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100% 0.0%
5	0.0%	0.7%	0.0%	0.0%	2.2%	0.7%	0.7%	0.0%	0.0%	0.0%	50.0% 50.0%
6	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	NaN% NaN%
7	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	NaN% NaN%
8	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	23.4%	4.4%	2.9%	76.2% 23.8%
9	1.5%	1.5%	0.7%	0.7%	0.0%	0.0%	0.0%	0.7%	8.0%	1.5%	55.0% 45.0%
10	0.7%	0.0%	0.0%	0.0%	0.0%	0.7%	0.0%	1.5%	2.9%	36.5%	86.2% 13.8%
	0.0% 100%	25.0% 75.0%	75.0% 25.0%	75.0% 25.0%	75.0% 25.0%	0.0% 100%	0.0% 100%	91.4% 8.6%	52.4% 47.6%	89.3% 10.7%	**75.2% 24.8%**

Figure 4.7: Confusion matrix for 2011 underground network

Figure 4.8 presents the continuous risk profile along with the actual accidents that occurred in 2011. This plot shows the continuous risk profile varying between 75% and 100%, however, with all the accidents occurring above 80% and again the continuous risk never spends much time below 80% risk over the year.

Next, the 2011 underground network was used to estimate the risk in the next year (2012) which was plotted along with the actual accidents in 2012 and this can be seen in Figure 4.9. From this plot it can be seen that the continuous risk profile varies between 75% and 100% with the majority between 80% and 100%. There are two outlying accidents, one at 79% and the other at 75% and the rest of the accidents all occur above 80%.

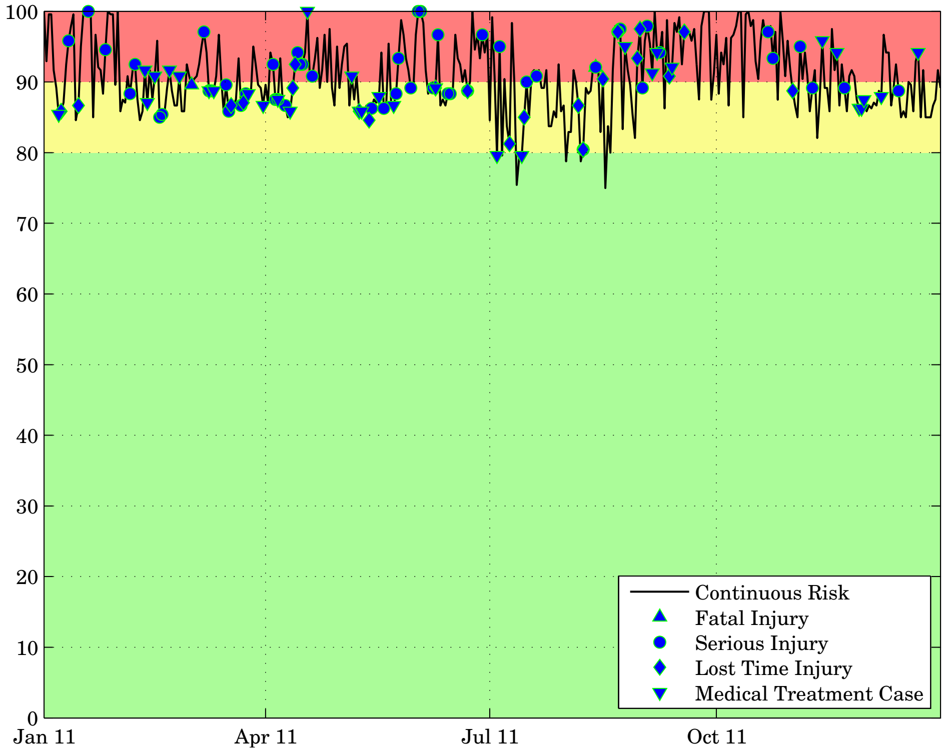


Figure 4.8: Continuous risk for 2011 underground section

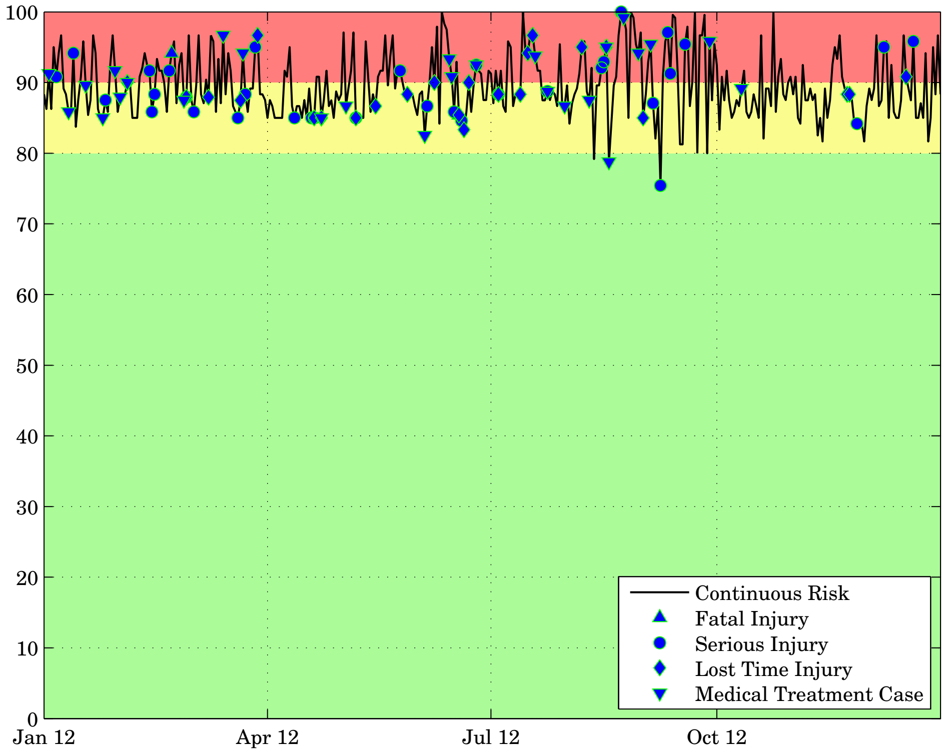


Figure 4.9: Predicted continuous risk for 2012 underground section

4.4.1.4 2012 underground network

In 2012 the underground section had 91 accidents which equates to roughly 1.8 accidents every week. Knowing that on average an accident occurred every four days, it is assumed that the networks calculated risk will almost always stay above 80% risk. The 2012 underground network created, similarly made use of the training setup of 70% data for network training, 25% data for network validation and 5% data for network testing along with twelve hidden nodes which resulted in the following training errors,

Table 4.5: MSE for 2012 underground network

	MSE
Training	0.0203
Validation	0.0461
Testing	0.0137
Total	0.0264

As can be seen, the network had a low training and testing errors and an average validation error, which resulted in a suitable total error. Next, the confusion matrix for the 2012 underground network is plotted in Figure 4.10, it shows that the majority of the misclassifications are close to the main diagonal and thus is not a problem. In the 2012 underground network confusion matrix, 8.7% of the classifications occur below the main diagonal and 10.5% of the classification occur above the main diagonal, thus the bias is 1.8% to lower output values, which is insignificant. This resulted in a training classification accuracy of 81.9% or an error of 18.1%.

Figure 4.11 presents the continuous risk profile along with the actual accidents that occurred in 2012. It shows that the continuous risk ranged between 51% and 100%, with the majority of the risk between 80% and 100%. Furthermore, all the accidents occur above 80%.

Next, this network was used to estimate the risk in the next year (2013) which was plotted along with the actual accidents in 2013 and this can be seen in Figure 4.12. This plot varies between 78% and 100%, with all the accidents occurring above 80%.

Output Class \ Target Class	1	2	3	4	5	6	7	8	9	10	
1	3.4%	0.0%	0.9%	0.9%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	80.0% 20.0%
2	0.0%	3.4%	0.9%	0.0%	0.9%	0.0%	0.0%	0.0%	0.0%	0.0%	66.7% 33.3%
3	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	NaN% NaN%
4	0.0%	0.0%	0.0%	2.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100% 0.0%
5	0.0%	0.0%	0.0%	0.9%	2.9%	1.7%	0.9%	0.0%	0.0%	0.0%	42.9% 57.1%
6	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	NaN% NaN%
7	0.0%	0.0%	1.7%	0.0%	0.0%	0.0%	0.9%	0.0%	0.0%	0.0%	33.3% 66.7%
8	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	20.7%	2.6%	1.7%	82.8% 17.2%
9	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	1.7%	18.1%	0.0%	91.3% 8.7%
10	0.0%	0.0%	0.0%	0.0%	0.0%	0.9%	0.0%	2.6%	0.9%	30.2%	87.5% 12.5%
	100% 0.0%	100% 0.0%	0.0% 100%	75.0% 25.0%	75.0% 25.0%	0.0% 100%	50.0% 50.0%	82.8% 17.2%	84.0% 16.0%	94.6% 5.4%	**81.9% 18.1%**

Figure 4.10: Confusion matrix for 2012 underground network

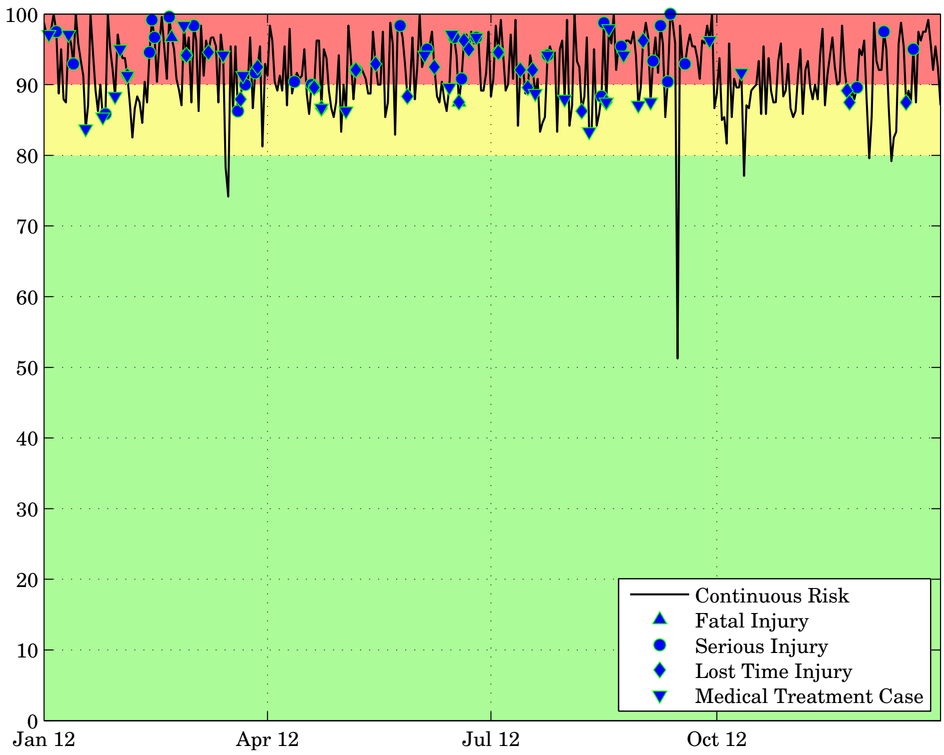


Figure 4.11: Continuous risk for 2012 underground section

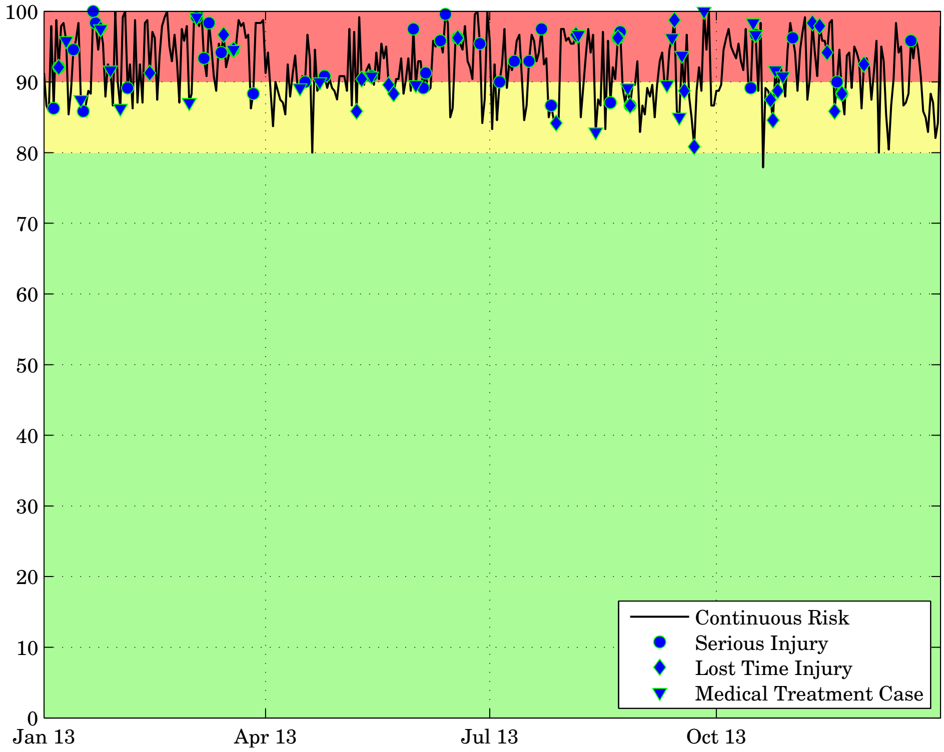


Figure 4.12: Predicted continuous risk for 2013 underground section

4.4.1.5 Underground networks summary

From looking at the figures of the continuous risk profiles of the four underground networks along with their predictions, they all are similar with the risk virtually never going below 80%. Thus despite all four networks statistically being accurate at predicting the majority of the accidents, no actual use is gained from these models, other than confirming that in the underground section there is constantly a very high risk of an accident occurring. Tables 4.6 and 4.7 are a summary of the statistics from the underground networks. Both tables present the year of the data used in the network on the top x-axis and for each of these, the network used, network error, number of accidents and percentage of outlying accidents is shown. Table 4.6 presents the values for the risk profiles with the data used in training the networks and Table 4.7 presents the values for the predicted risk profiles.

From Tables 4.6 and 4.7 it can be seen that the 2010 network is the best with respect to it having the lowest training error, however, the 2012 network is the best with respect to having the least percentage of outlying accidents. Furthermore, due to all the networks continuous risk profile staying constantly above 80%, no one network can be identified as better than another one. Next, networks for the four years for the engineering section of the mine are trained and validated.

Table 4.6: Summary of underground networks

	2009	**2010**	**2011**	**2012**	**Average**
Network	2009	2010	2011	2012	
Network training % error	22.2%	17.9%	24.8%	18.1%	20.8%
Number of accidents	128	98	112	91	107
% outliers	6.25%	2.04%	1.79%	0.00%	2.52%

Table 4.7: Summary of underground networks predictions

	2010	**2011**	**2012**	**2013**	**Average**
Network	2009	2010	2011	2012	
Network training % error	22.2%	17.9%	24.8%	18.1%	20.8%
Number of accidents	98	112	91	93	99
% outliers	0.00%	0.00%	1.79%	0.00%	0.45%

4.4.2 Engineering

The engineering section contributed 117 accidents to the total (741) of non-duplicated accidents, this was made up from 39 in 2009, 20 in 2010, 20 in 2011, 19 in 2012 and 19 in 2013. These accidents along with the created converse arguments were used in training the models below. The accident numbers over the five years drop significantly from 2009 to 2010, however, from 2010 to 2013 the accident numbers stayed fairly constant. Next, the four engineering networks are trained and validated.

4.4.2.1 2009 engineering network

In 2009 the engineering section had 39 accidents which equates to roughly one accident every 1.3 weeks. Knowing that on average an accident occurred every nine days, it is assumed that the networks calculated risk will often be close to or above 80% risk. The 2009 engineering network created made use of a training setup of 75% data for network training, 25% data for network validation and 0% data for network testing along with thirteen hidden nodes which resulted in the training errors seen in Table 4.8.

As can be seen from the errors, the 2009 network had a similar low error for the training, validation and testing, which resulted in an acceptable error for the total network. Next, the confusion matrix is plotted in Figure 4.13 to identify where the misclassifications occurred in the training. From the confusion matrix it is seen that the majority of the data is correctly classified (along the main diagonal) and the majority of the misclassifications are close

Table 4.8: MSE for 2009 engineering network

	MSE
Training	0.0222
Validation	0.0285
Total	0.0238

to the main diagonal, implying that they are close to their actual value. There are very few major misclassification and they predominantly occurred as low target values being classified as a high output value. Since the majority of the misclassifications occur below the main diagonal, it is assumed the network will be biased more towards higher outputs. 12.6% of the classifications occur below the main diagonal and 8.4% of the classifications occur above the main diagonal, thus there is a bias of 4.2% towards a higher output. This resulted in a classification accuracy of 78.9% or a network training error of 21.1%.

Output Class \ Target Class	1	2	3	4	5	6	7	8	9	10	
1	2.1%	0.0%	0.0%	1.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	60.0% 40.0%
2	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	NaN% NaN%
3	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	NaN% NaN%
4	0.0%	0.0%	2.8%	0.7%	0.7%	1.4%	0.7%	0.0%	0.0%	0.0%	11.1% 88.9%
5	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	NaN% NaN%
6	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	NaN% NaN%
7	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	NaN% NaN%
8	0.7%	0.7%	0.0%	0.7%	0.7%	0.0%	0.7%	31.7%	0.0%	4.2%	80.4% 19.6%
9	0.0%	0.0%	0.0%	0.0%	0.7%	0.0%	0.0%	0.0%	19.0%	0.0%	96.4% 3.6%
10	0.0%	2.1%	0.0%	0.0%	0.7%	0.7%	0.0%	2.1%	0.0%	25.4%	31.8% 18.2%
	75.0% 25.0%	0.0% 100%	0.0% 100%	25.0% 75.0%	0.0% 100%	0.0% 100%	0.0% 100%	93.8% 6.3%	100% 0.0%	85.7% 14.3%	**78.9%** **21.1%**

Figure 4.13: Confusion matrix for 2009 engineering network

Next, Figure 4.14 shows the calculated continuous risk profile along with the actual accidents that occurred in 2009, this was used in the training described previously. From this plot it can be seen that the continuous risk varies between 25% and 100%, however, the majority if the risk lies above 80% as expected due to the number of accidents. The actual accidents that occurred in 2009 are plotted on the continuous risk line and this shows two major outliers that occur 48% risk and there are five accidents which occur just below the 80% risk, however, due to the random nature of accidents, it is assumed that there will be some outliers that cannot be predicted. Although there are sections where the risk is above 80% and no accidents occurred, this does not imply an inaccurate model, the immeasurable component of human variability is also involved in the occurrence of accidents, thus for the exact same measured conditions an accident could happen one day and not the next. Excluding the two major outliers and assuming the five accidents just below the 80% are 80%, 26 of the accidents occur at a risk between 80% and 90% and 12 accidents occur at a risk between 90% and 100%. Another interesting observation is that of the 39 accidents, 23 of them occur when the risk has a positive gradient or is at a peak, which effectively is the turning point from a positive gradient.

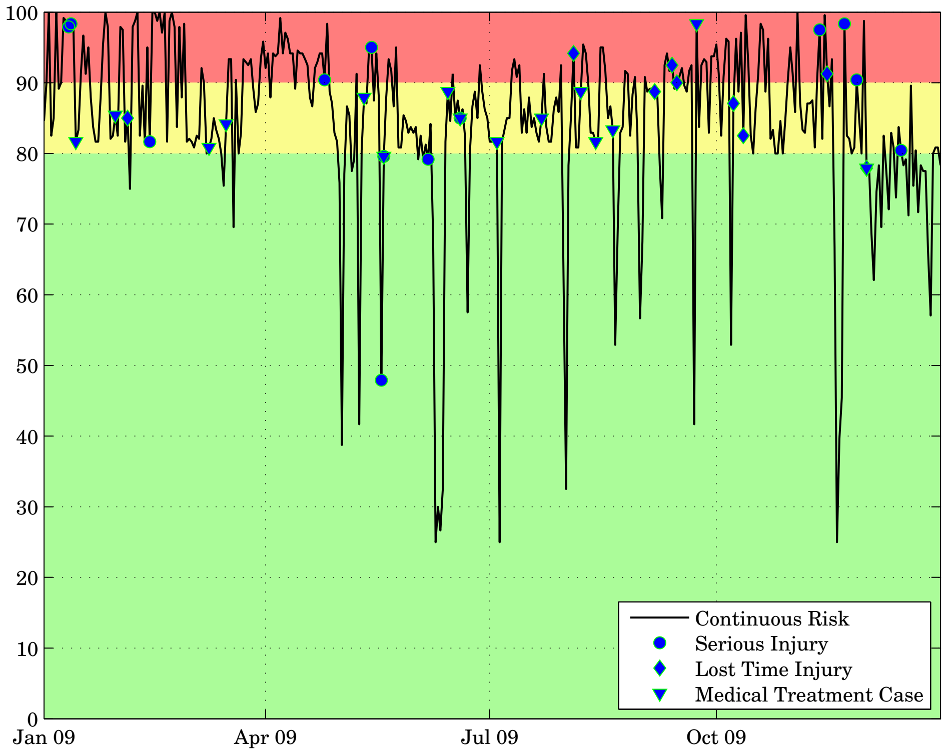


Figure 4.14: Continuous risk for 2009 engineering section

Next, this network was used to estimate the risk in the next year (2010) which was plotted along with the actual accidents in 2010 and this can be seen in Figure 4.15. This plot shows again that the continuous risk varies between 25% and 100%, however, the majority if the risk lies above 80%, similar to the trained 2009 continuous risk. However, this time there is only one outlying accident which is a LTI which occurs at roughly 58%. This time, besides for the one outlier, 9 accidents occurred between 80% and 90% risk and 10 accidents occurred between 90% and 100% risk and 15 of the 20 accidents occur while the continuous risk has a positive gradient or is at a peak. Interestingly, from the 1st April 2010 to the 1st July 2010 no accidents occurred in the engineering section and this is the section were the model had the large dips, although there were still peaks above 80% in this time period.

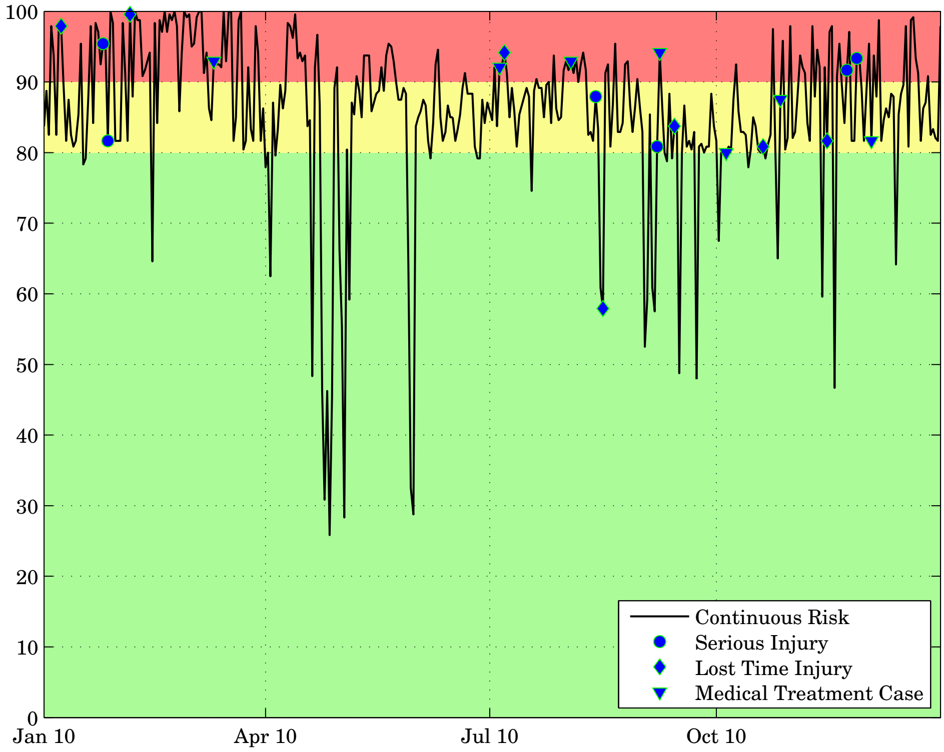


Figure 4.15: Predicted continuous risk for 2010 engineering section

It can be seen from these figures that the majority of the time the risk lies above 80% as was expected due to the network being trained with 39 accidents in the span of one year. Furthermore, as is desired, almost all of the accidents occur at a risk of greater than 80%.

4.4.2.2 2010 engineering network

In 2010 the engineering section had 20 accidents which equates to roughly one accident every two and a half weeks. Knowing that on average an accident occurred every eighteen days, it is assumed that the networks calculated risk will not stay above the 80% risk as much as it did in the 2009 network. The 2010 engineering network created made use of the training setup of 70% data for network training, 30% data for network validation and 0% data for network testing along with fourteen hidden nodes which resulted in the training errors seen in Table 4.9.

Table 4.9: MSE for 2010 engineering network

	MSE
Training	0.0279
Validation	0.0368
Total	0.0306

As can be seen from the errors, the network had a lower training error than validation error, resulting in an acceptable total error despite it being larger than the total error for the 2009 network. Next, Figure 4.16 shows the confusion matrix associated to this network. The confusion matrix showed some misclassifications and of the misclassifications, the majority were close to the main diagonal which is better than them further away from the main diagonal. This time 7.2% of the classifications occurred below the main diagonal and 21.2% occurred above the main diagonal, showing a bias towards lower outputs of 14%. This resulted in the trained models accuracy being 71.8%, or having an error of 28.2%.

Output Class \ Target Class	1	2	3	4	5	6	7	8	9	10	
1	3.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100% 0.0%
2	0.0%	2.4%	2.4%	0.0%	0.0%	0.0%	0.0%	3.5%	0.0%	0.0%	28.6% 71.4%
3	0.0%	0.0%	1.2%	0.0%	0.0%	0.0%	0.0%	3.5%	0.0%	0.0%	25.0% 75.0%
4	0.0%	0.0%	1.2%	4.7%	0.0%	0.0%	0.0%	3.5%	0.0%	0.0%	50.0% 50.0%
5	0.0%	0.0%	0.0%	0.0%	3.5%	1.2%	0.0%	0.0%	0.0%	0.0%	75.0% 25.0%
6	0.0%	0.0%	0.0%	0.0%	0.0%	1.2%	0.0%	0.0%	0.0%	0.0%	100% 0.0%
7	0.0%	0.0%	0.0%	0.0%	1.2%	0.0%	2.4%	0.0%	0.0%	0.0%	66.7% 33.3%
8	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	24.7%	0.0%	0.0%	100% 0.0%
9	1.2%	2.4%	0.0%	0.0%	0.0%	1.2%	0.0%	0.0%	24.7%	7.1%	67.7% 32.3%
10	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	14.1%	100% 0.0%
	75.0% 25.0%	50.0% 50.0%	25.0% 75.0%	100% 0.0%	75.0% 25.0%	33.3% 66.7%	100% 0.0%	57% 42.9%	100% 0.0%	66.7% 33.3%	**71.8%** **28.2%**

Figure 4.16: Confusion matrix for 2010 engineering network

Figure 4.17 presents the continuous risk profile along with the actual accidents that occurred in 2010. This figure shows that the continuous risk varies between 35% and 97%, with the majority of the risk varying between 70% and 97%. There is one outlying accident which is a MTC that occurs at 73% risk, furthermore, 10 accidents occurred between 80% and 90% and 9 of the accidents occur between 90% and 100% risk. Five of the six SI's occur above 90% risk and the rest of the accidents occur at a risk between 80% and 97%. This time 9 of the 20 accidents occurred when the continuous risk gradient was positive.

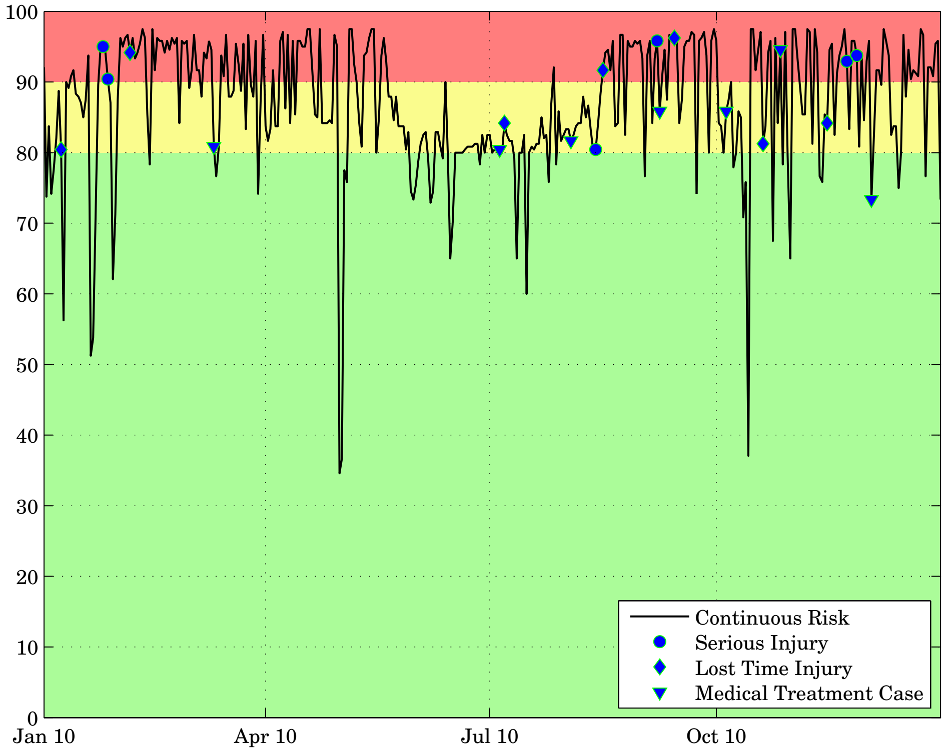


Figure 4.17: Continuous risk for 2010 engineering section

Next, this network was used to estimate the risk in the next year (2011) which was plotted along with the actual accidents in 2011 and this can be seen in Figure 4.18. This plot ranges between 40% and 97%, with the majority of the risk staying above 80%. There are two outlying accidents which are both LTI's which occur at 69% and 73% risk, however, the rest of the accidents occur within the 80% to 100% band. Besides for the two outliers, 10 accidents occur between 90% and 100% risk and 8 accidents occur between 80% and 90% risk. Furthermore, 13 of the 20 accidents occur when the risk profile is increasing.

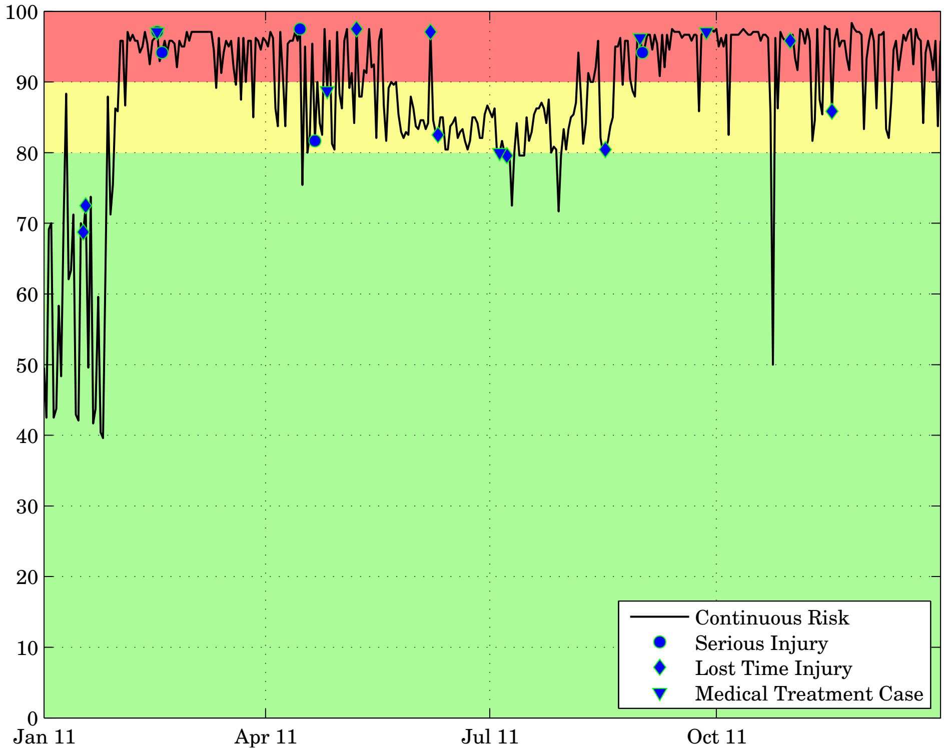


Figure 4.18: Predicted continuous risk for 2011 engineering section

4.4.2.3 2011 engineering network

In 2011 the engineering section had 20 accidents which equates to roughly one accident every two and a half weeks. Knowing that on average an accident occurred every eighteen days, it is assumed that the network will respond similarly to the 2010 network. Again, the 2011 engineering network created made use of the training setup of 70% data for training, 30% data for validation and 0% data for testing, however, along with twelve hidden nodes this time which resulted in the following training errors,

Table 4.10: MSE for 2011 engineering network

	MSE
Training	0.0211
Validation	0.0339
Total	0.0250

As can be seen, the network had a sufficiently low training, validation, and total error, which resulted in a suitable network. Then the confusion matrix for this network was plotted in Figure 4.19 and it shows that the majority of the misclassifications occur close to the main diagonal and as such are not a problem. Furthermore, 15.4% of the classifications occurred below the main diagonal and 7.2% of the classifications occurred above the main diagonal, thus the bias is shifted to 8.2% towards higher output values. This resulted in a training classification accuracy of 77.6% or an error of 22.4%.

Output Class \ Target Class	1	2	3	4	5	6	7	8	9	10	
1	4.7%	0.0%	1.2%	1.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	66.7% / 33.3%
2	0.0%	1.2%	0.0%	1.2%	2.4%	0.0%	1.2%	0.0%	0.0%	0.0%	20.0% / 80.0%
3	0.0%	1.2%	3.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	75.0% / 25.0%
4	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	NaN% / NaN%
5	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	NaN% / NaN%
6	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	NaN% / NaN%
7	0.0%	1.2%	0.0%	2.4%	0.0%	0.0%	1.2%	0.0%	0.0%	0.0%	25.0% / 75.0%
8	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	14.1%	0.0%	0.0%	100% / 0.0%
9	0.0%	1.2%	0.0%	0.0%	2.4%	3.5%	0.0%	0.0%	31.8%	0.0%	81.8% / 18.2%
10	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	3.5%	0.0%	21.2%	85.7% / 14.3%
	100% / 0.0%	25.0% / 75.0%	75.0% / 25.0%	0.0% / 100%	0.0% / 100%	0.0% / 100%	50.0% / 50.0%	80.0% / 20.0%	100% / 0.0%	100% / 0.0%	**77.6% / 22.4%**

Figure 4.19: Confusion matrix for 2011 engineering network

Figure 4.20 presents the continuous risk profile along with the actual accidents that occurred in 2011. This plot shows the continuous risk profile varying between 10% and 100%, however, with the majority above 80%. Only one accident occurs below 80%, 12 accidents occur between 80% and 90%, and 7 accidents occur between 90% and 100% risk. Furthermore, of the six SI's, five occur above 90% risk and now 16 of the 20 accidents occur when the continuous risk profile gradient is positive.

Next, the 2011 engineering network was used to estimate the risk in the next year (2012) which was plotted along with the actual accidents in 2012 and this can be seen in Figure 4.21. From this plot it can be seen that the continuous risk profile varies between 10% and 100% with the majority between 80% and 100%. There is one outlying accident that occurs at 67% risk, then 12 of the accidents occur at a risk between 80% and 90% and 6 accidents occur at a risk between 90% and 100%. Furthermore, 14 of the 19 accidents occur when the continuous risk profile is positive.

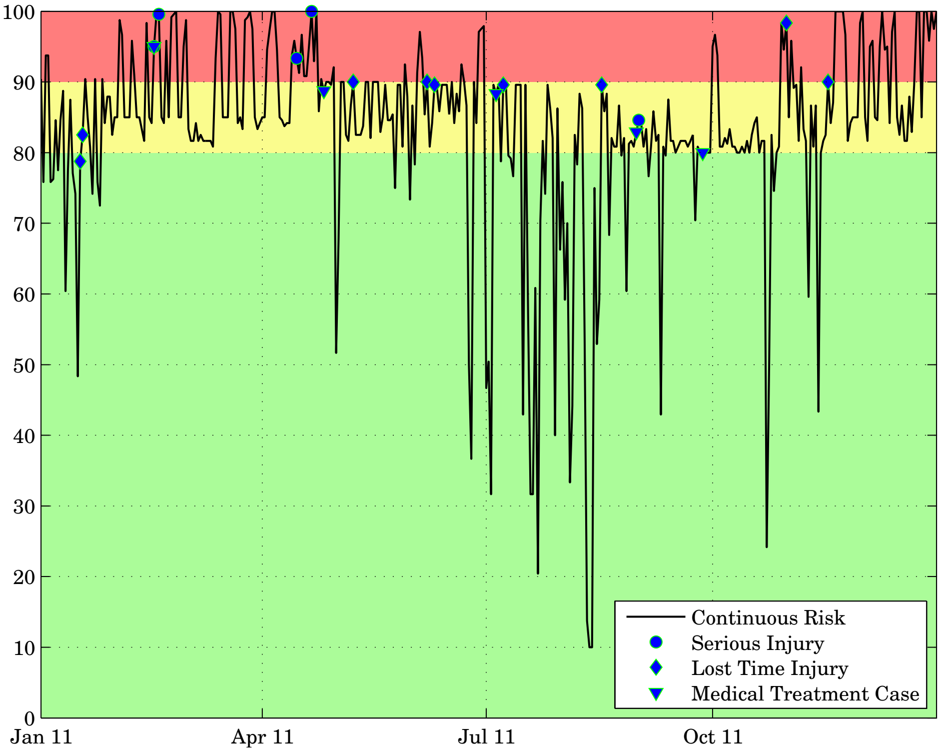


Figure 4.20: Continuous risk for 2011 engineering section

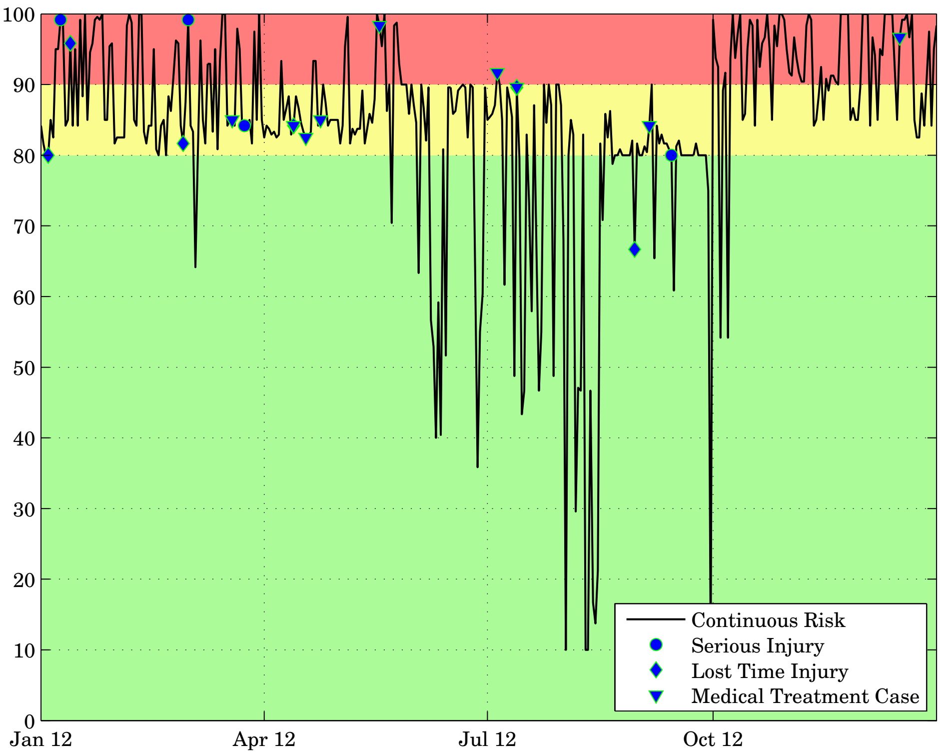


Figure 4.21: Predicted continuous risk for 2012 engineering section

4.4.2.4 2012 engineering network

In 2012 the engineering section had 19 accidents which equates to roughly one accident ever 2.7 weeks. Knowing that on average an accident occurred every 19 days, it is assumed again that the network will respond similarly to the 2010 and 2011 networks. The 2012 engineering network created made use of the training setup of 70% data for network training, 25% data for network validation and 5% data for network testing along with fourteen hidden nodes which resulted in the following training errors,

Table 4.11: MSE for 2012 engineering network

	MSE
Training	0.0128
Validation	0.0190
Testing	0.0675
Total	0.0170

As can be seen, the network had sufficiently low training and validation errors and despite the testing error being rather high, this is due to the fact that so few examples are used in the network testing, for example, if there are four examples used in the network testing, if two are misclassified, then the percentage error would be 50%. Next, the confusion matrix for the 2012 engineering network is plotted in Figure 4.22, it shows that the majority of the misclassifications are close to the main diagonal and thus is not a big problem. In the 2012 engineering network confusion matrix, 7.3% of the classifications occur below the main diagonal and 8.4% of the classifications occur above the main diagonal, thus the bias is 1.1% to lower output values, which is insignificant. This resulted in a training classification accuracy of 84.1% or an error of 15.9%.

Figure 4.23 presents the continuous risk profile along with the actual accidents that occurred in 2012. It shows that the continuous risk ranged between 20% and 93%, with the majority of the risk between 60% and 90%. Furthermore, there are four accidents that occur below 80% risk (60%, 70%, 78% and 79%), however, only two of these are major outliers. Thus, assuming the two non-major outliers are close enough to the 80% boundary, 14 of the accidents occur at a risk between 80% and 90% and 3 accidents occur at a risk between 90% and 100% and of the 19 accidents present in 2012, 12 of them occur when the continuous risk profile gradient is positive.

Next, this network was used to estimate the risk in the next year (2013) which was plotted along with the actual accidents in 2013 and this can be seen in Figure 4.24. This plot varies between 31% and 92%, with the majority of the continuous risk between 60% and 90%. This time there are four outlying

Figure 4.22: Confusion matrix for 2012 engineering network

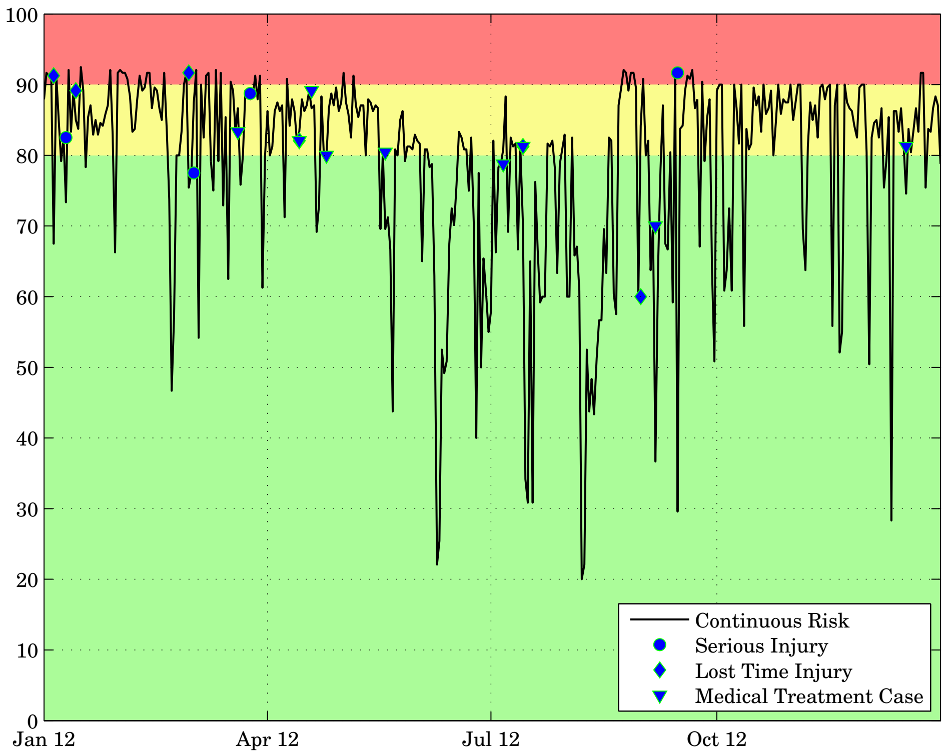


Figure 4.23: Continuous risk for 2012 engineering section

accidents (64%, 69%, 73% and 75%), 14 accidents that occur at a risk between 80% and 90%, one accident that occurs at a risk between 90% and 100% and 13 of the 19 accidents occur when the continuous risk profile is positive.

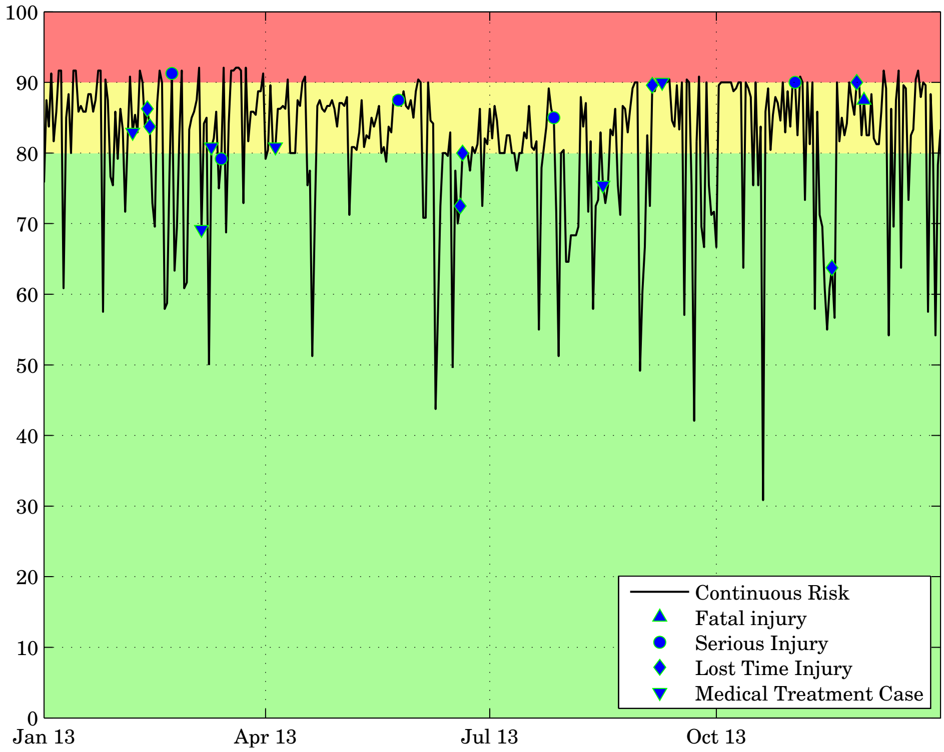


Figure 4.24: Predicted continuous risk for 2013 engineering section

4.4.2.5 Engineering networks summary

From looking at the figures of the continuous risk profiles of the four engineering networks along with their predictions, the 2012 network appears to be the best network and the 2010 network appears to be the worst network. This agrees with the network training errors, where the 2012 network had the lowest error (15.9%) and the 2010 network had the largest error (28.2%). However, from a statistical point of view the same conclusions cannot be drawn. Tables 4.12 and 4.13 are a summary of the statistics from the engineering networks. Both tables present the year of the data used in the network on the top x-axis and for each of these, the network used, network error, number of accidents, percentage of outlying accidents, percentage of accidents occurring at a risk between 80% and 90%, percentage of accidents occurring at a risk between 90% and 100% and the percentage of accidents that occurred when the continuous risk profile is positive is shown. Table 4.12 presents the values for the risk profiles with the data used in training the networks and Table 4.13 presents the values for the predicted risk profiles.

Table 4.12: Summary of engineering networks

	2009	**2010**	**2011**	**2012**	**Average**
Network	2009	2010	2011	2012	
Network training % error	21.1%	28.2%	22.4%	15.9%	21.9%
Number of accidents	39	20	20	19	25
% outliers	5.13%	5.00%	5.00%	10.53%	6.42%
% between 80% and 90%	64.10%	50.00%	60.00%	73.68%	61.95%
% between 90% and 100%	30.77%	45.00%	35.00%	15.79%	31.64%
% with positive gradient	58.97%	45.00%	80.00%	63.16%	61.78%

Table 4.13: Summary of engineering networks predictions

	2010	**2011**	**2012**	**2013**	**Average**
Network	2009	2010	2011	2012	
Network training % error	21.1%	28.2%	22.4%	15.9%	21.9%
Number of accidents	20	20	19	19	20
% outliers	5.00%	10.00%	5.26%	21.05%	10.33%
% between 80% and 90%	45.00%	40.00%	63.16%	73.68%	55.46%
% between 90% and 100%	50.00%	50.00%	31.58%	5.26%	34.21%
% with positive gradient	75.00%	65.00%	73.68%	68.42%	70.53%

From Tables 4.12 and 4.13 it can be seen that the 2009 and 2011 are the better networks with respect to having the lowest percentage of outlying accidents, however, these are the networks in the middle with average network training errors of 21.1% and 22.4% respectively. Furthermore, the 2011 network has very high percentages for accidents occurring while the continuous risk profile has a positive gradient. The average percentage of accidents occurring while the continuous risk profile is positive for the trained networks is 61.78% and for the predictive networks is 70.53% and thus it appears that the gradient of the risk profile is a warning signal in addition to the actual risk value. From this, statistically it appears that the 2011 engineering network is the best network. Next, networks for the four years for the other sections of the mine are trained and validated.

4.4.3 Other

The other sections contributed 102 accidents to the total (741) of non-duplicated accidents, this was made up from 33 in 2009, 18 in 2010, 11 in 2011, 17 in 2012 and 23 in 2013. These accidents along with the converse arguments were used in training the networks below. The accident numbers over the five years drop significantly from 2009 to 2011, however, from 2011 to 2013 the accident numbers started to rise again. Next, the four other sections networks are trained and validated.

4.4.3.1 2009 other network

In 2009 the other section had 33 accidents which equates to roughly one accident every one and a half weeks. Knowing that on average an accident occurred every eleven days, it is assumed that the networks calculated risk will often be close to or above 80% risk. The 2009 other network created, made use of the training setup of 70% data for network training, 25% data for network validation and 5% data for network testing along with twelve hidden nodes which resulted in the following training errors,

Table 4.14: MSE for 2009 other network

	MSE
Training	0.0170
Validation	0.0406
Testing	0.0206
Total	0.0231

As can be seen, the network had sufficiently low training and testing errors and despite the validation error not being as low, this still yielded a satisfactory total error. Next, the confusion matrix for the 2009 other network is plotted in Figure 4.25, it shows that the majority of the misclassifications are close to the main diagonal and thus is not a big problem. In the 2009 other network confusion matrix, 12.8% of the classifications occur below the main diagonal and 7.2% of the classifications occur above the main diagonal, thus the bias is 5.6% towards higher output values. This resulted in a training classification accuracy of 79.8% or an error of 20.2%.

Figure 4.26 presents the continuous risk profile along with the actual accidents that occurred in 2009. It shows that the continuous risk ranged between 26% and 96%, with the majority of the risk between 50% and 90%. Furthermore, there are five accidents that occur below 80% risk, however, only four of these are major outliers (60%, 70%, 71%, and 75%). Additionally, the three SI's occur at a risk of 84%, 91% and 90% and all the LTI's occur at a risk between 80% and 90%, besides for one outlier occurring at 75% and the MTC's vary between 78% and 91% besides for the three outliers mentioned above. Lastly, of the 33 accidents present in 2009, 20 of them occur when the continuous risk profile gradient is positive.

Output Class \ Target Class	1	2	3	4	5	6	7	8	9	10	
1	2.4%	0.0%	0.8%	0.8%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	60.0% 40.0%
2	0.0%	1.6%	0.0%	0.8%	2.4%	0.0%	0.0%	0.0%	2.4%	0.0%	22.2% 77.8%
3	0.0%	0.8%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0% 100%
4	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	NaN% NaN%
5	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	NaN% NaN%
6	0.0%	0.0%	0.0%	0.0%	0.0%	0.8%	0.0%	0.0%	0.0%	0.0%	100% 0.0%
7	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	NaN% NaN%
8	0.0%	0.8%	0.8%	0.8%	0.8%	0.8%	0.8%	41.1%	0.0%	0.0%	89.5% 10.5%
9	0.0%	0.0%	0.0%	0.8%	0.0%	0.8%	0.8%	2.4%	26.6%	0.0%	84.6% 15.4%
10	0.8%	0.0%	1.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	7.3%	75.0% 25.0%
	75.0% 25%	50.0% 50%	0.0% 100%	0.0% 100%	0.0% 100%	33.3% 66.7%	0.0% 100%	94.4% 5.6%	91.7% 8.3%	100% 0.0%	**79.8% 20.2%**

Figure 4.25: Confusion matrix for 2009 other network

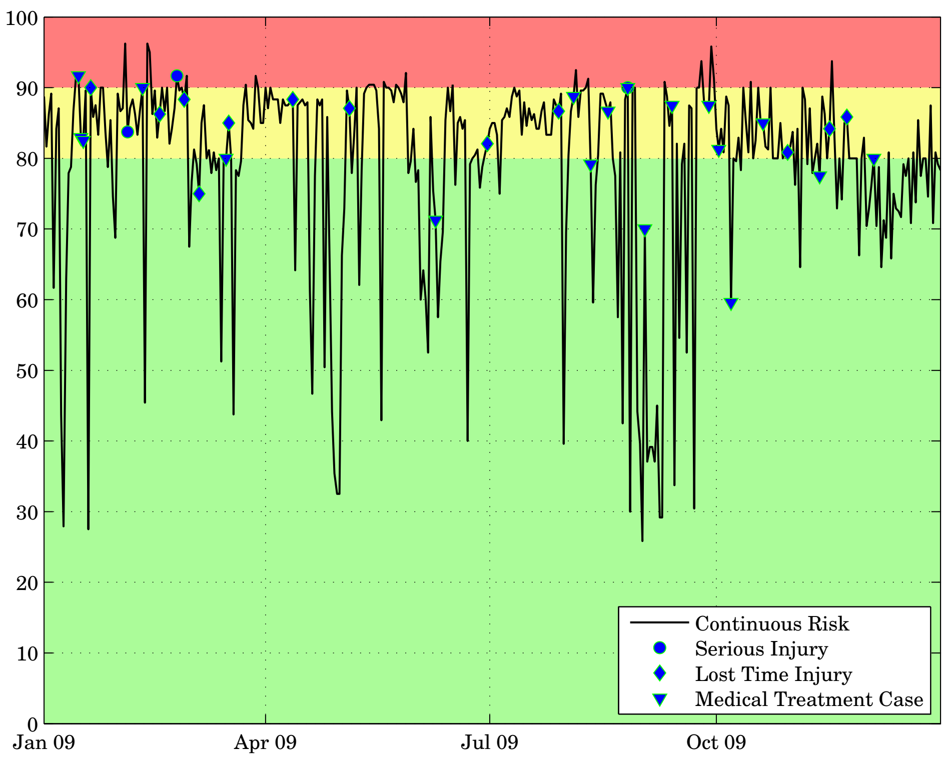


Figure 4.26: Continuous risk for 2009 other section

Next, this network was used to estimate the risk in the next year (2010) which was plotted along with the actual accidents in 2010 and this can be seen in Figure 4.27. This plot varies between 21% and 96%, with the majority of the continuous risk between 70% and 90%. This time there are three outlying accidents, two MTC's at approximately 76% and 77% and a SI at approximately 73%. The rest of the accidents occur at a risk between 80% and 90% and 11 of the 18 accidents occur when the continuous risk profile is positive.

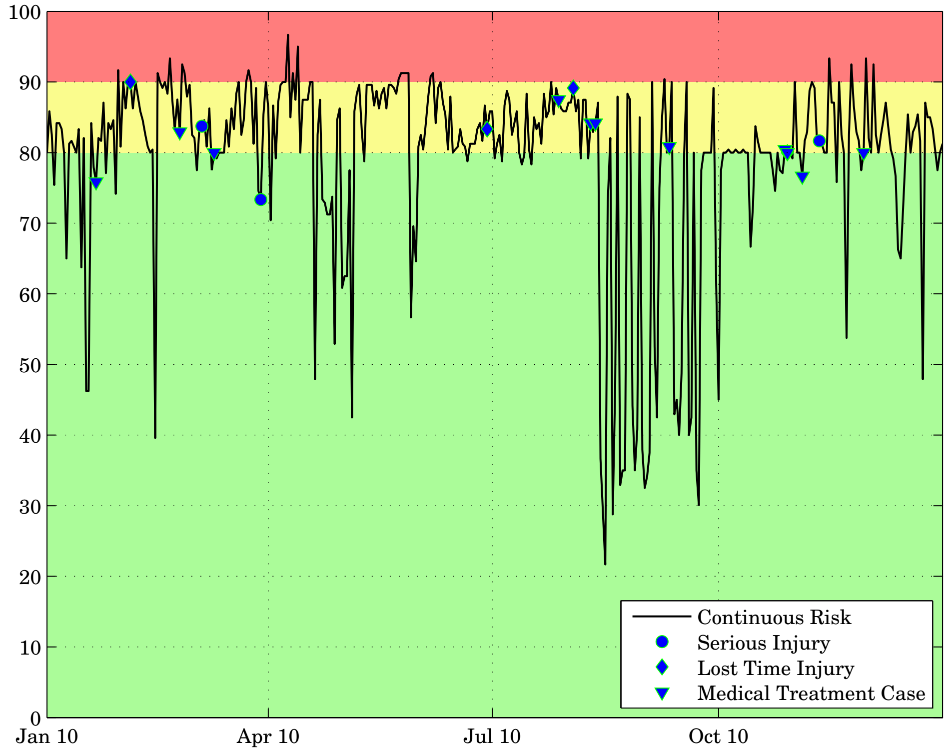


Figure 4.27: Predicted continuous risk for 2010 other section

4.4.3.2 2010 other network

In 2010 the other section had 18 accidents which equates to roughly one accident every three weeks. Knowing that on average an accident occurred every twenty days, it is assumed that the networks calculated risk will occasionally be close to or above 80% risk. However, in 2010 the accidents appeared to occur in three clusters with gaps of no accidents in between the clusters, thus the continuous risk may be higher than expected. Again, the 2010 other network created made use of the training setup of 75% data for training, 25% data for validation and 0% data for testing along with fourteen hidden nodes which resulted in the training errors seen in Table 4.15.

As can be seen, the network had a moderate training, validation and total error, however, the network was able to generalise well. Then the confusion

Table 4.15: MSE for 2010 other network

	MSE
Training	0.0455
Validation	0.0533
Total	0.0474

matrix for this network was plotted in Figure 4.28 and it shows that the majority of the misclassifications occur close to the main diagonal and as such are not a problem, except for the network misclassifying 24% of the examples as a 10% to 20% risk. Furthermore, 15.4% of the classifications occurred below the main diagonal and 24.8% of the classifications occurred above the main diagonal, thus the network is biased by 9.4% towards lower output values. This resulted in a training classification accuracy of 59.8% or an error of 40.2%.

Figure 4.28: Confusion matrix for 2010 other network

Figure 4.29 presents the continuous risk profile along with the actual accidents that occurred in 2010. This plot shows the continuous risk profile varying between 50% and 100%, however, with the majority between 70% and 90%. Only two accidents occur below 80% (66% and 78%), 15 accidents occur between 80% and 90% and one accident occurs above 90%. Furthermore, 11 of the 18 accidents occur when the continuous risk profile gradient is positive.

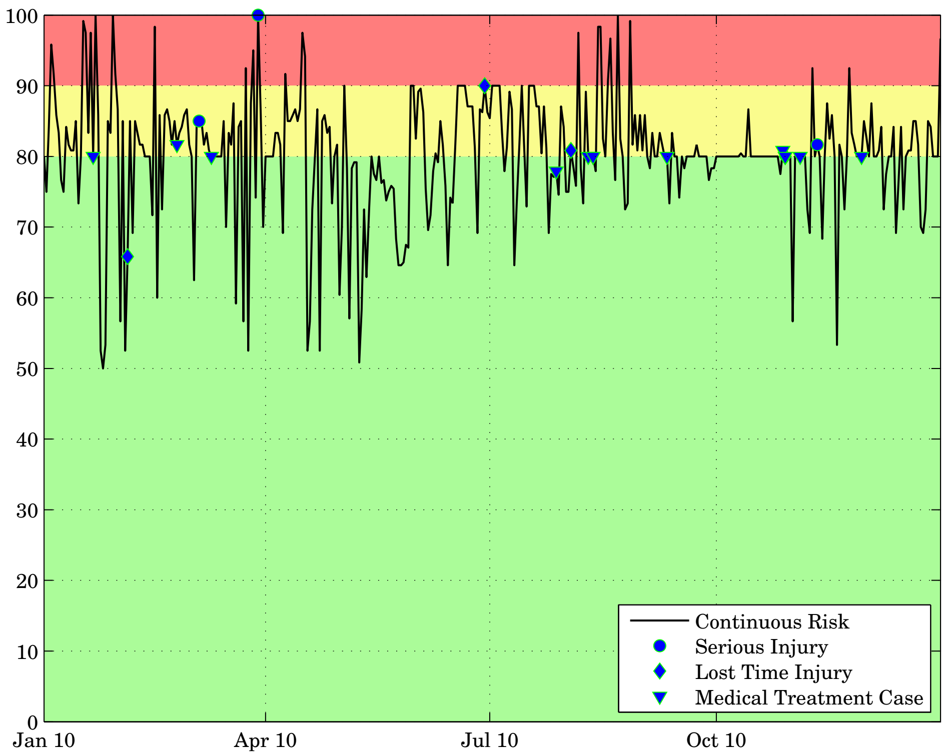


Figure 4.29: Continuous risk for 2010 other section

Next, the 2010 other network was used to estimate the risk in the next year (2011) which was plotted along with the actual accidents in 2011 and this can be seen in Figure 4.30. From this plot it can be seen that the continuous risk profile varies between 30% and 100% with the majority of the risk between 80% and 100%. There are no outlying accidents, eight accidents occur between 80% and 90% and three accidents occur above 90%. Furthermore, 6 of the 11 accidents occur when the continuous risk profile is positive.

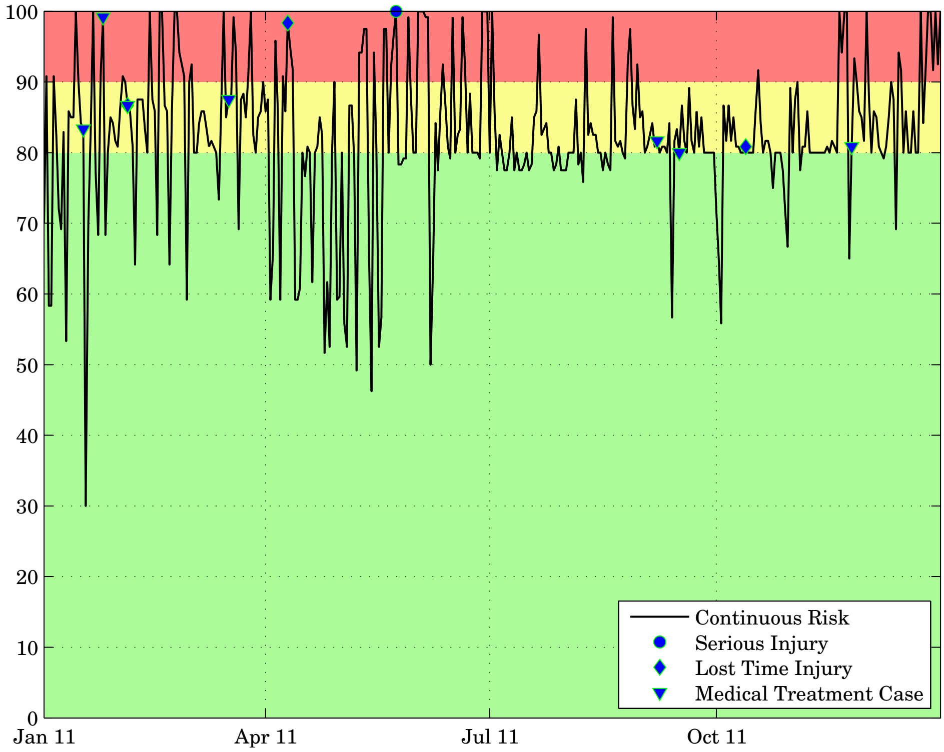


Figure 4.30: Predicted continuous risk for 2011 other section

4.4.3.3 2011 other network

In 2011 the other section had 11 accidents which equates to roughly one accident every month. Knowing that on average an accident occurred every thirty three days, it is assumed that the networks calculated risk will rarely be close to or above 80% risk. The 2011 other network created made use of the training setup of 80% data for network training, 20% data for network validation and 0% data for network testing along with fourteen hidden nodes which resulted in the following training errors,

Table 4.16: MSE for 2011 other network

	MSE
Training	0.0256
Validation	0.0271
Total	0.0259

As can be seen from the errors, the network had a sufficiently low training and validation error, which resulted in a satisfactory total error. Next, Figure 4.31 shows the confusion matrix associated to this network. The confusion matrix showed very few misclassifications, however, again the network had a few misclassifications where the network predicted the 10% to 20% risk incorrectly. From the confusion matrix, 8.8% of the classifications occurred below the main diagonal and 15.4% occurred above the main diagonal, thus showing a bias towards lower outputs of 6.6%. This resulted in the trained models accuracy being 75.8%, or having an error of 24.2%.

Output Class \ Target Class	1	2	3	4	5	6	7	8	9	10	
1	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	NaN% NaN%
2	4.4%	3.3%	3.3%	3.3%	4.4%	3.3%	1.1%	0.0%	0.0%	0.0%	14.3% 85.7%
3	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	NaN% NaN%
4	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	NaN% NaN%
5	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	NaN% NaN%
6	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	NaN% NaN%
7	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	NaN% NaN%
8	0.0%	1.1%	1.1%	0.0%	0.0%	0.0%	0.0%	46.2%	0.0%	0.0%	95.5% 4.5%
9	0.0%	0.0%	0.0%	1.1%	0.0%	0.0%	1.1%	0.0%	19.8%	0.0%	90.0% 10.0%
10	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	6.6%	100% 0.0%
	0.0% 100%	75.0% 25.0%	0.0% 100%	0.0% 100%	0.0% 100%	0.0% 100%	0.0% 100%	100% 0.0%	100% 0.0%	100% 0.0%	**75.8%** **24.2%**

Figure 4.31: Confusion matrix for 2011 other network

Figure 4.32 presents the continuous risk profile along with the actual accidents that occurred in 2011. This figure shows that the continuous risk varies between 20% and 100% with the majority of the risk below 80%. There is one outlying accident occurring at 75% risk and the one SI occurs at 100% and the other nine accidents all occur between 80% and 90% risk. This time 10 of the 11 accidents occurred when the continuous risk gradient was positive.

Next, this network was used to estimate the risk in the next year (2012) which was plotted along with the actual accidents in 2012 and this can be seen in Figure 4.33. This plot ranges between 20% and 100% and there are three outlying accidents which occur at 48%, 59% and 75% risk. Then one accident occurs above 90% risk, and 13 accidents occur between 80% and 90% risk. Furthermore, 8 of the 17 accidents occur when the risk profile is increasing.

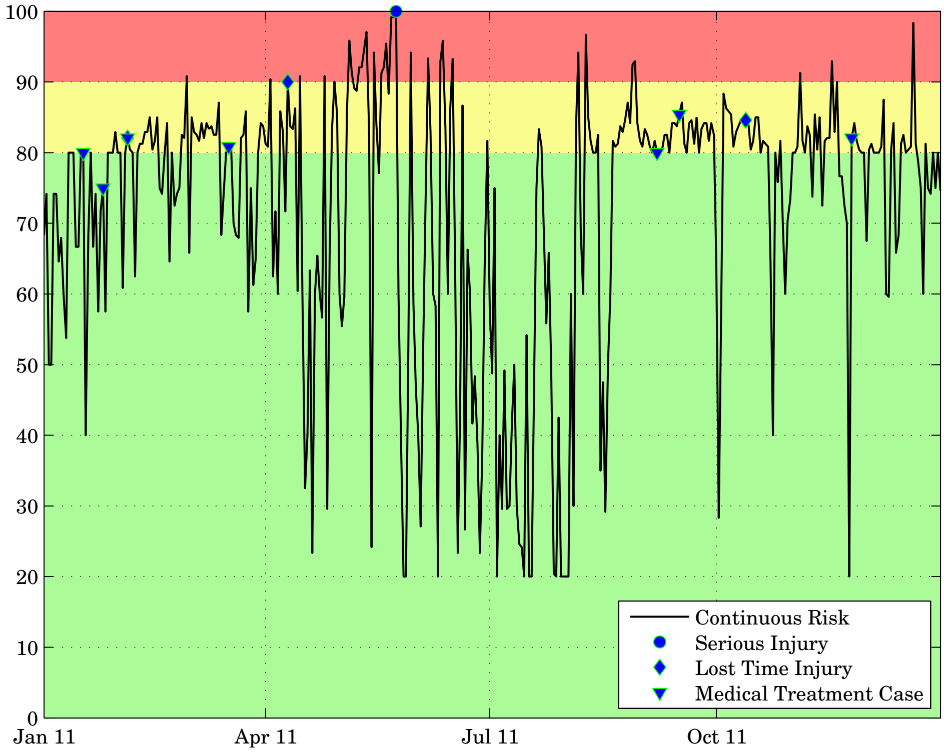


Figure 4.32: Continuous risk for 2011 other section

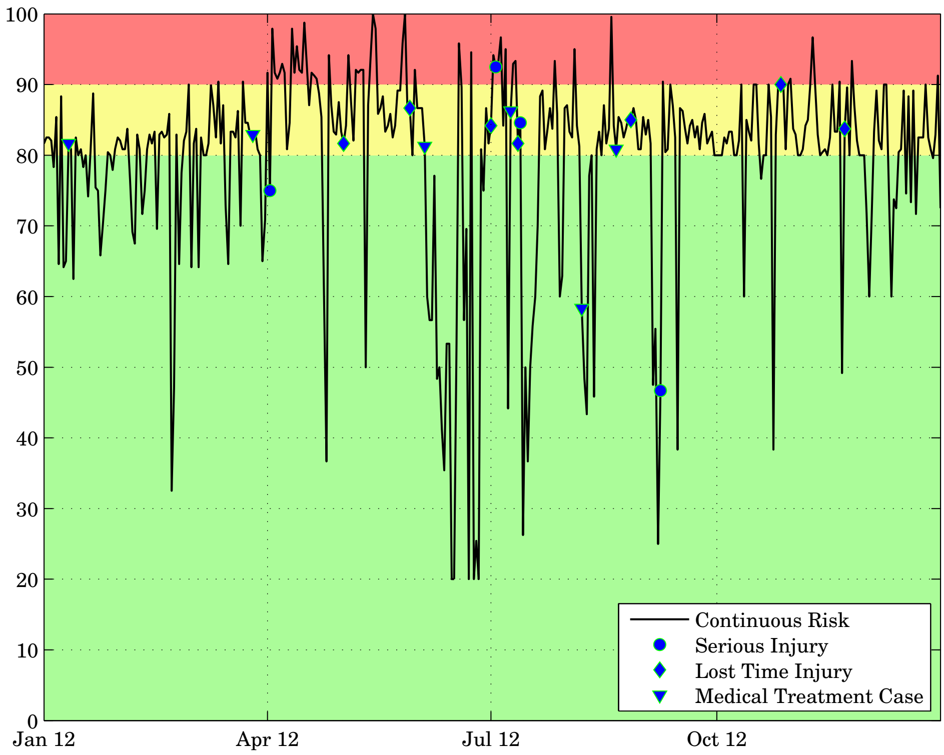


Figure 4.33: Predicted continuous risk for 2012 other section

4.4.3.4 2012 other network

In 2012 the other section had 17 accidents which equates to roughly one accident every three weeks. Knowing that on average an accident occurred every twenty one days, it is assumed that the networks calculated risk will occasionally be close to or above 80% risk, however, most of the accidents occur close together and then leave a large gap of no accidents before the next cluster of accidents, thus the output may be higher than expected. The 2012 other network created, made use of the training setup of 70% data for network training, 25% data for network validation and 5% data for network testing along with twelve hidden nodes which resulted in the following training errors,

Table 4.17: MSE for 2012 other network

	MSE
Training	0.0132
Validation	0.0353
Testing	0.0453
Total	0.0204

As can be seen, the network had sufficiently low training error, and average validation and testing errors, which resulted in a satisfactory total error. Next, the confusion matrix for the 2012 other network is plotted in Figure 4.34, it shows that the majority of the misclassifications are close to the main diagonal and thus is not a big problem. In the 2012 other network confusion matrix, 11% of the classifications occur below the main diagonal and 6.6% of the classifications occur above the main diagonal, thus the bias is 4.4% towards higher output values. This resulted in a training classification accuracy of 82.8% or an error of 17.2%.

Figure 4.35 presents the continuous risk profile along with the actual accidents that occurred in 2012. It shows that the continuous risk ranged between 44% and 100%, with the majority of the risk between 60% and 100%. Furthermore, no accidents occurred below 80% risk, seven accidents occurred between 80% and 90% risk and ten accidents occurred above 90% risk. Lastly, of the 17 accidents present in 2012, 13 of them occur when the continuous risk profile gradient is positive.

Next, this network was used to estimate the risk in the next year (2013) which was plotted along with the actual accidents in 2013 and this can be seen in Figure 4.36. This plot varies between 44% and 100%, with the majority of the continuous risk between 60% and 100%. This time there are three outlying accidents, two MTC's at approximately 62% and 75% and a LTI at approximately 74%. Of the rest of the accidents, four occur between 80%

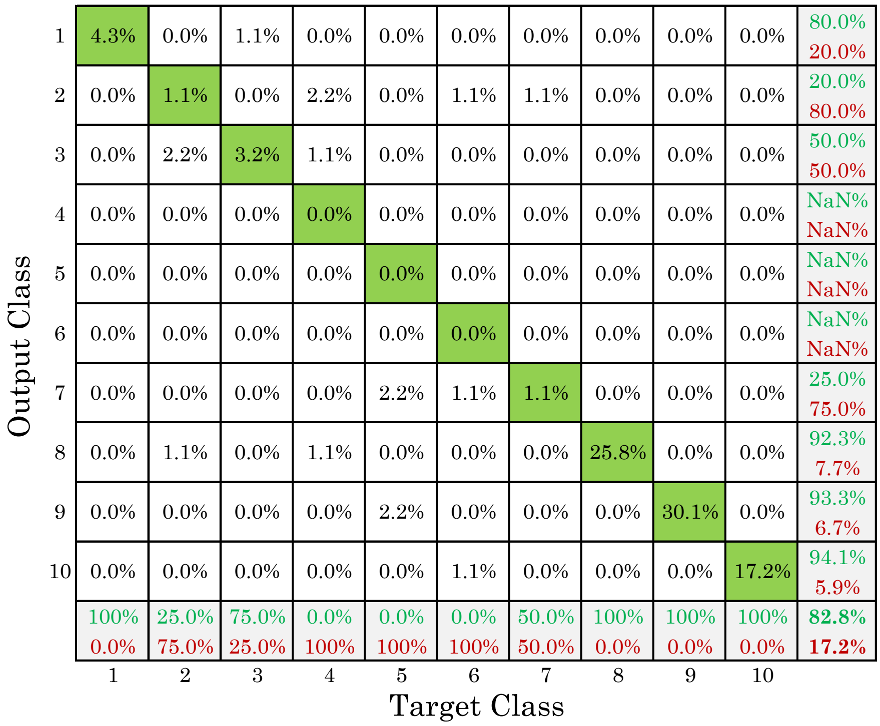


Figure 4.34: Confusion matrix for 2012 other network

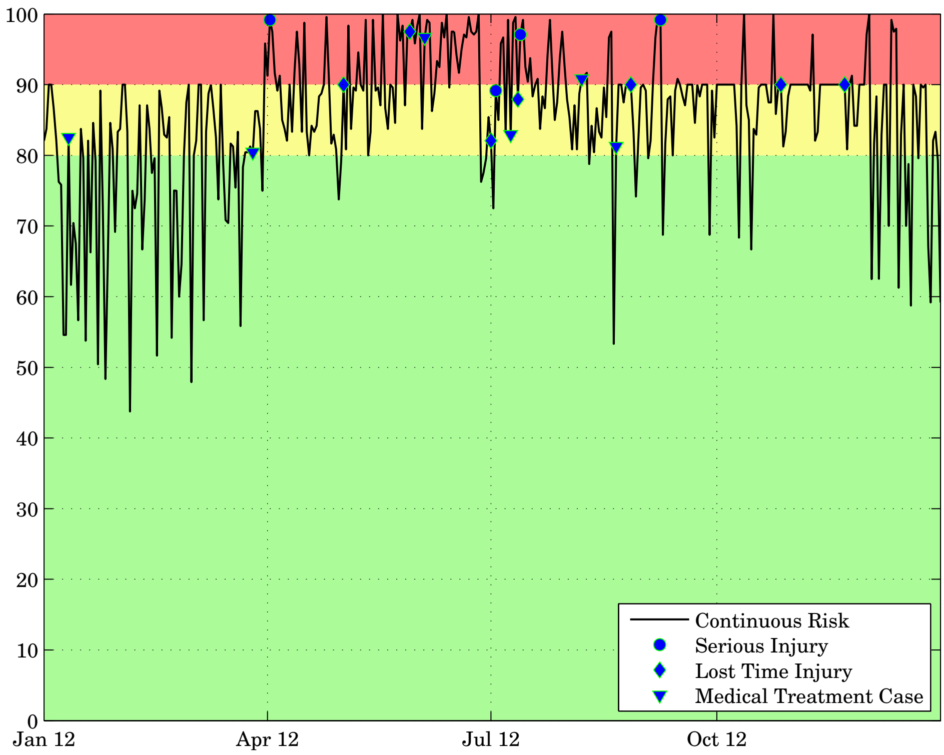


Figure 4.35: Continuous risk for 2012 other section

and 90% risk and 16 accidents occur above 90%. Furthermore, 16 of the 23 accidents occur when the continuous risk profile is positive.

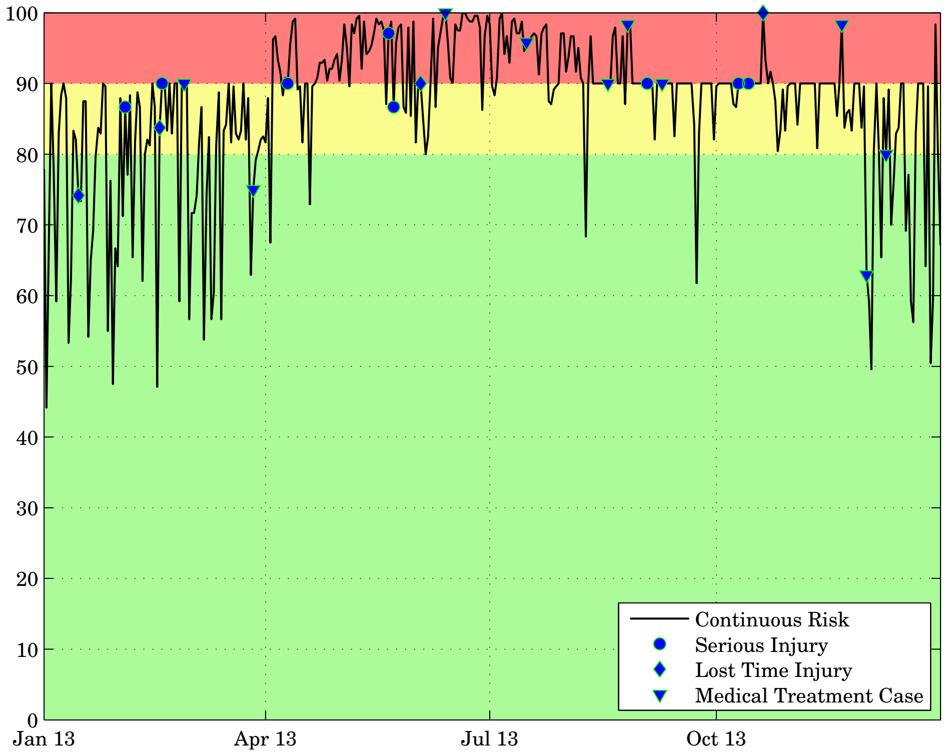


Figure 4.36: Predicted continuous risk for 2013 other section

4.4.3.5 Other networks summary

From looking at the figures of the continuous risk profiles of the four other networks along with their predictions, the 2011 network appears to be the best network and the 2010 network appears to be the worst network. This agrees with the network training error for the 2010 network which had the worst network error which was 40.2%, however, the 2011 network had the third best training error of the other networks which was 24.2%. Furthermore, from a statistical point of view the same conclusions cannot be drawn. Tables 4.18 and 4.19 are a summary of the statistics from the other networks. Both tables present the year of the data used in the network on the top x-axis and for each of these, the network used, network error, number of accidents, percentage of outlying accidents, percentage of accidents occurring at a risk between 80% and 90%, percentage of accidents occurring at a risk between 90% and 100% and the percentage of accidents that occurred when the continuous risk profile is positive is shown. Table 4.18 presents the values for the risk profiles with the data used in training the networks and Table 4.19 presents the values for the predicted risk profiles.

Table 4.18: Summary of other networks

	2009	**2010**	**2011**	**2012**	**Average**
Network	2009	2010	2011	2012	
Network training % error	20.2%	40.2%	24.2%	17.2%	25.5%
Number of accidents	33	18	11	17	20
% outliers	12.12%	11.11%	9.09%	0.00%	8.08%
% between 80% and 90%	81.82%	83.33%	81.82%	41.18%	72.04%
% between 90% and 100%	6.06%	5.56%	9.09%	58.82%	19.88%
% with positive gradient	60.61%	61.11%	90.91%	76.47%	72.28%

Table 4.19: Summary of other networks predictions

	2010	**2011**	**2012**	**2013**	**Average**
Network	2009	2010	2011	2012	
Network training % error	20.2%	40.2%	24.2%	17.2%	25.5%
Number of accidents	18	11	17	23	17
% outliers	16.67%	0.00%	17.65%	13.04%	11.84%
% between 80% and 90%	83.33%	72.73%	5.88%	17.39%	44.83%
% between 90% and 100%	0.00%	27.27%	76.47%	69.57%	43.33%
% with positive gradient	61.11%	54.55%	47.06%	69.57%	58.07%

From Tables 4.18 and 4.19 it can be seen that the 2010 and 2012 networks are the better networks with respect to having the lowest percentage of outlying accidents, despite the 2010 network having the worst training error. Furthermore, the 2012 network has very high percentages for accidents occurring while the continuous risk profile has a positive gradient, thus for the other section, statistically it appears that the 2012 network is the best. The average percentage of accidents occurring while the continuous risk profile is positive for the trained networks is 72.28% which is higher than that of the engineering trained networks and for the predictive networks the average percentage of accidents occurring while the continuous risk profile is positive is 58.07% which is lower than that of the engineering predictive networks and thus again it appears that the gradient of the risk profile is a warning signal in addition to the actual risk value. Next, a sensitivity analysis is performed for all the networks and they are compared.

4.5 Sensitivity Analysis

As was discussed in the previous chapter, the sensitivity analysis was performed in three steps, firstly the mean values of each input attribute is calculated, next the network output for these mean inputs is computed and lastly, one input attribute at a time is varied to its maximum and minimum values and the network output is computed for each scenario. This resulted in 17 network outputs computed for each network, Table 4.20 presents the network output values for all the variations for the four engineering, four other and four underground networks, along with the mean values, as well as maxima and minima amongst the networks.

From Table 4.20, it can be seen that the average output for the networks range between 40% and 100% and the average over all the networks created is 77.5%. Furthermore, looking at all the other scenarios, the maximum and minimum outputs over all the networks ranges a lot, however, all the mean values appear to be in a similar range. Figure 4.37 presents a box and whiskers plot of the outputs from the sensitivity analysis for each input variable. The solid black line is the average network output line, then for each box, the whiskers represents the maximum and minimum outputs across all the networks, the top of the box represents the maximum average output per input attribute and the bottom of the box represents the minimum average output per input attribute and lastly, the mean value of each box is the mean value between the maximum and minimum average values per attribute.

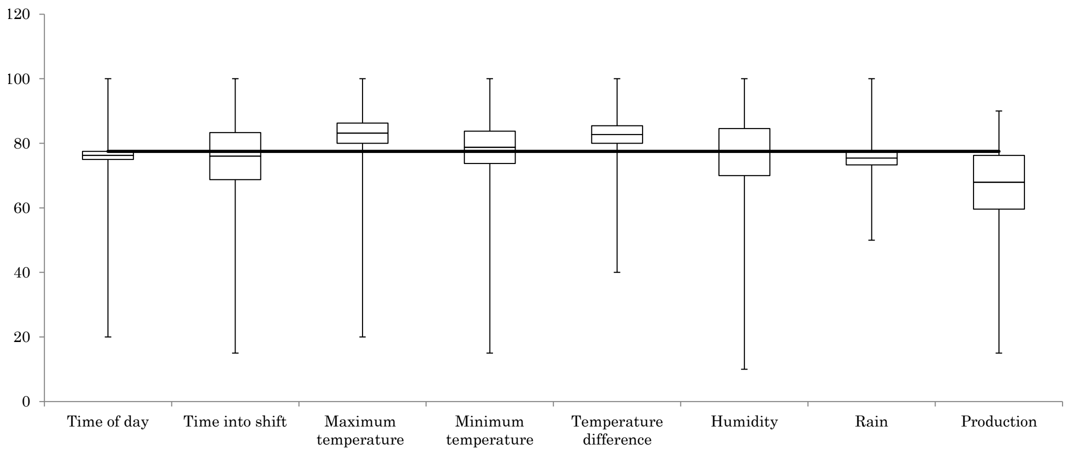


Figure 4.37: Sensitivity analysis for all networks created

From Figure 4.37, by ignoring the whiskers and only looking at the boxes, from the averages it appears that the production rate, humidity and time into the shift appear to have the largest influence on the networks output. Furthermore, it appears that the time of day and rainfall have the smallest influence on the networks output. Due to the underground networks not being useful because of the risk constantly staying above 80%, if the underground networks are omitted from the box and whiskers plot, this will result in a new

Table 4.20: Summary of network output values from sensitivity analysis

Section	Network	Average	Time of day		Time into shift		Max temp		Min temp		Temp diff		Humidity		Rain		Production	
			max	min	max	min	max	min	max	min	max	min	max	min	max	min	max	min
Engineering	2009	90	90	90	90	50	90	80	90	80	85	90	90	90	50	90	45	90
	2010	90	90	85	90	85	95	85	85	85	85	90	80	85	90	80	50	85
	2011	55	100	95	90	100	100	50	100	50	90	100	100	10	95	55	15	55
	2012	50	20	50	55	50	90	50	55	45	55	50	80	55	50	50	15	50
Other	2009	90	45	20	90	15	20	90	90	15	90	60	90	45	55	80	80	90
	2010	80	90	80	80	80	100	80	80	100	80	80	100	80	50	80	90	80
	2011	40	40	65	40	40	80	60	55	60	100	40	35	40	60	60	60	40
	2012	90	90	100	100	90	90	100	90	100	90	100	100	90	90	90	80	90
Underground	2009	80	80	80	100	80	100	100	90	90	80	85	80	80	85	80	80	80
	2010	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	90	80
	2011	100	90	100	100	100	100	100	100	90	90	100	90	100	90	100	60	90
	2012	85	85	85	85	55	90	85	90	90	100	85	90	85	85	85	50	85
Statistics	Mean	77.5	75	77.5	83.3	68.8	86.3	80	83.8	73.8	85.4	80	84.6	70	73.3	77.5	59.6	76.3
	Max	100	100	100	100	100	100	100	100	100	100	100	100	100	95	100	90	90
	Min	40	20	20	40	15	20	50	55	15	55	40	35	10	50	50	15	40

box and whiskers plot as can be seen in Figure 4.38. From Figure 4.38, again

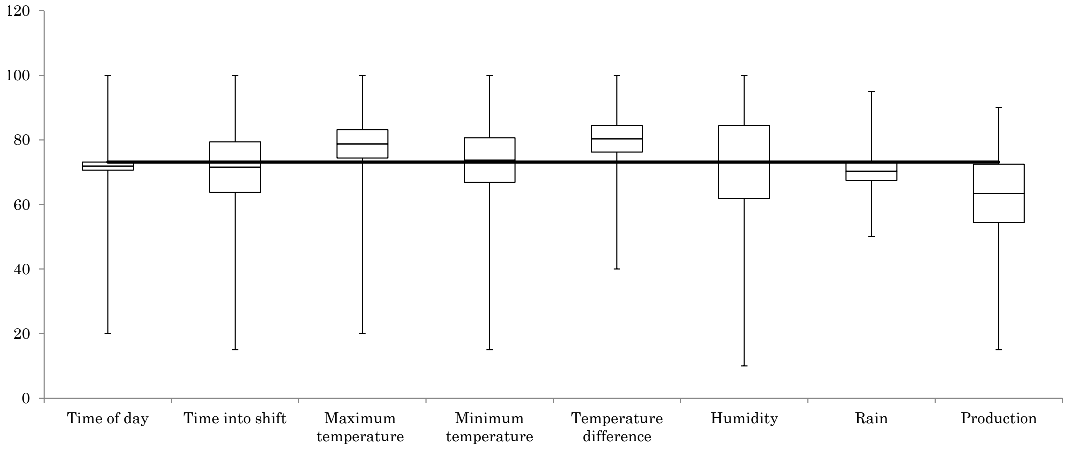


Figure 4.38: Sensitivity analysis for engineering and other sections

it can be seen that humidity, time into shift and production rate appear to have the largest influence in the output and again the rain and time of day appear to have the smallest influence over the continuous risk output.

4.6 Validation of Network Split

From the engineering networks section above it was identified that the 2011 engineering network was the best network. In order to identify why a network was created each year, rather than one generic network, the 2011 network, being the best engineering network, was used to predict the continuous risk profile for every year from 2009 to 2013 along with the accidents for each year overlaid onto the figures. As was expected, the 2011 engineering network predicted the accidents in 2011 and 2012 very well with only one outlying accident in each year. However, going forward to 2013, the network was conservative and the risk stayed above 80% the majority of the year and there were no outlying accidents and going backward in time, the continuous risk profile gets progressively worse. In 2010, the continuous risk profile varies largely and there are eight outlying accidents, and then in 2009, it gets even worse and there are 16 outlying accidents. Figures 4.39 to 4.43 present these outputs from 2009 to 2013 respectively.

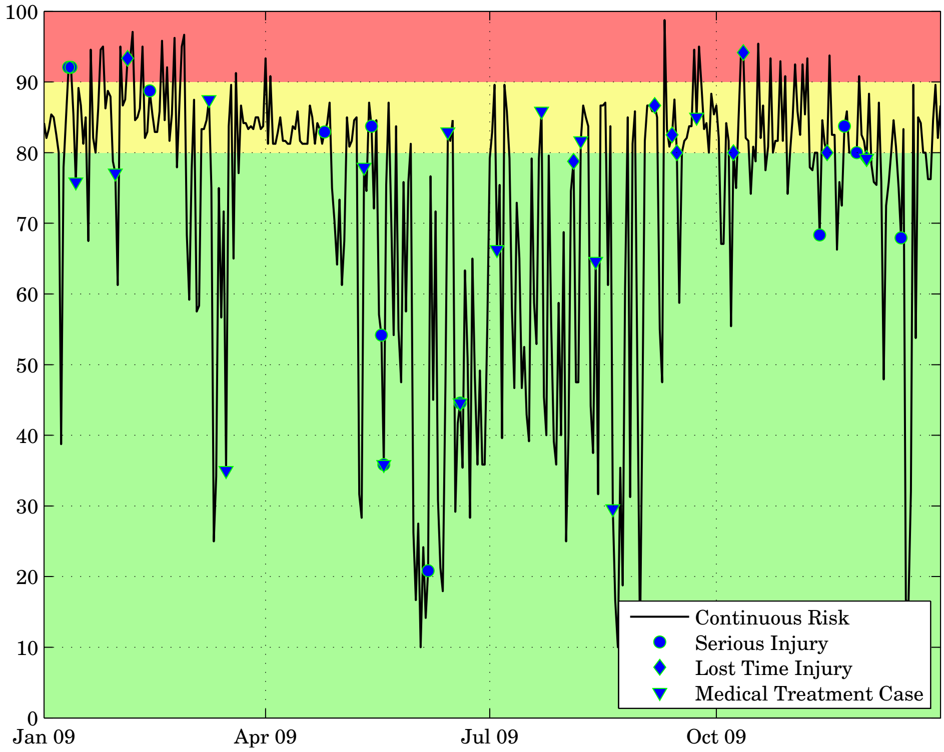


Figure 4.39: Engineering 2011 network predicting 2009 risk

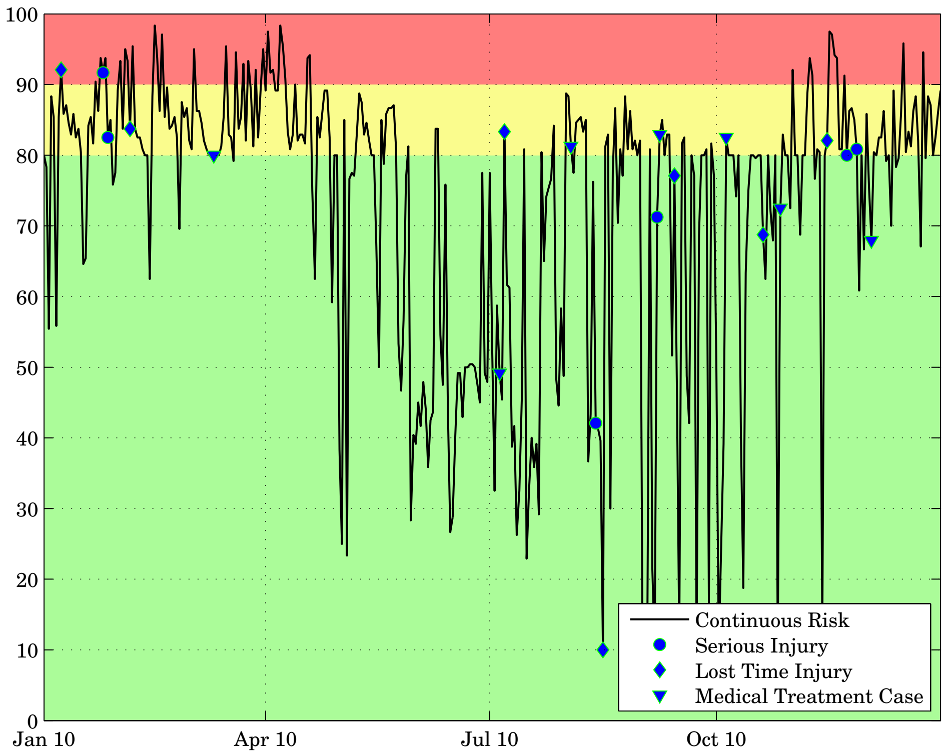


Figure 4.40: Engineering 2011 network predicting 2010 risk

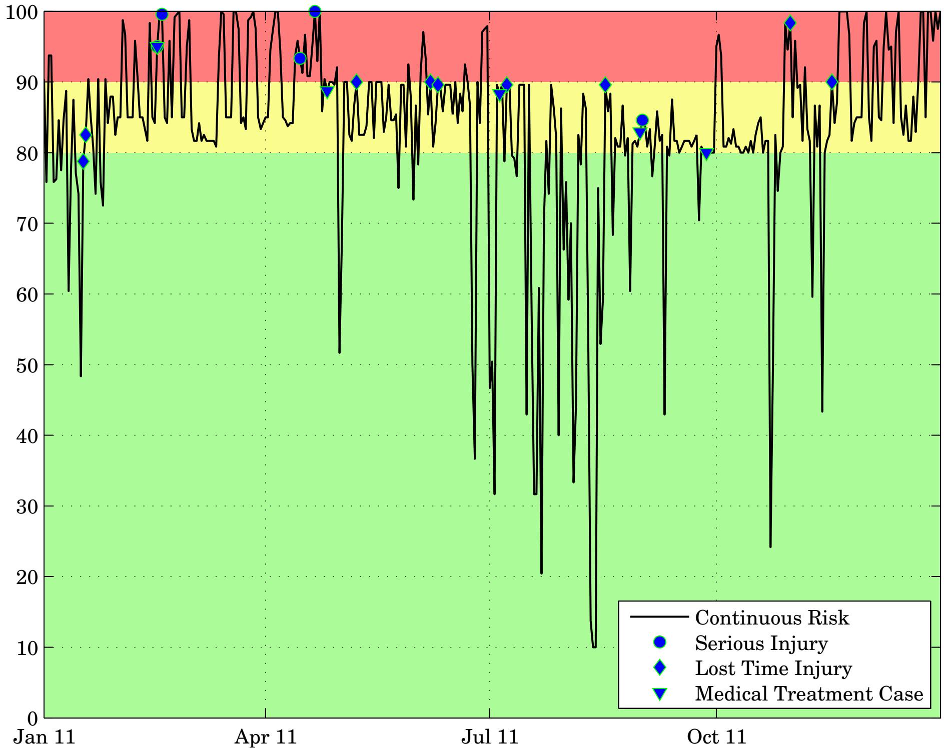


Figure 4.41: Engineering 2011 network predicting 2011 risk

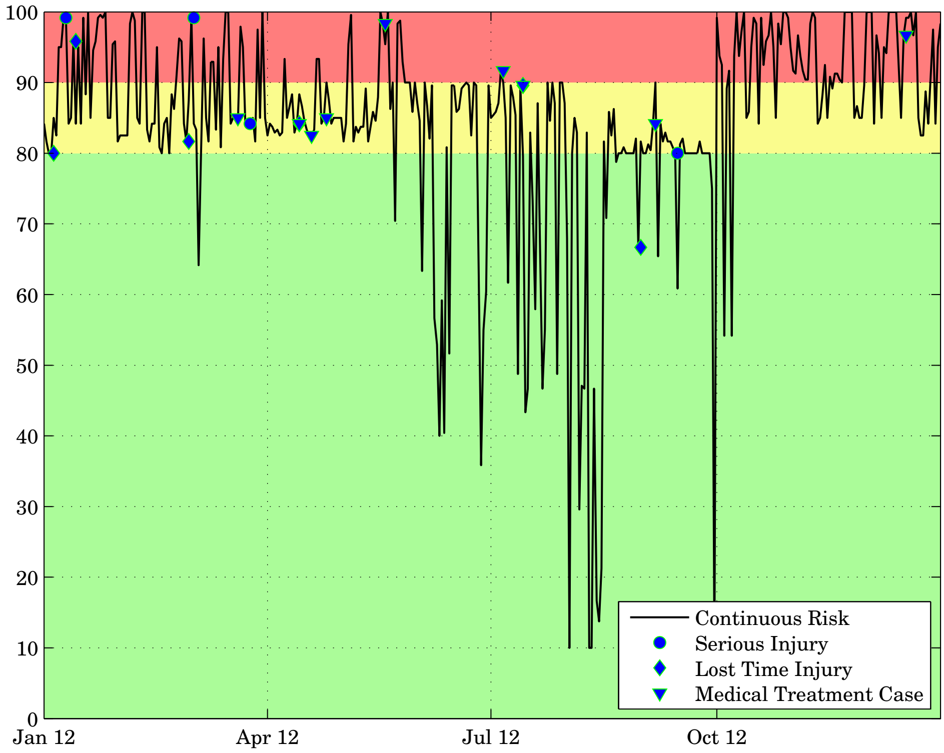


Figure 4.42: Engineering 2011 network predicting 2012 risk

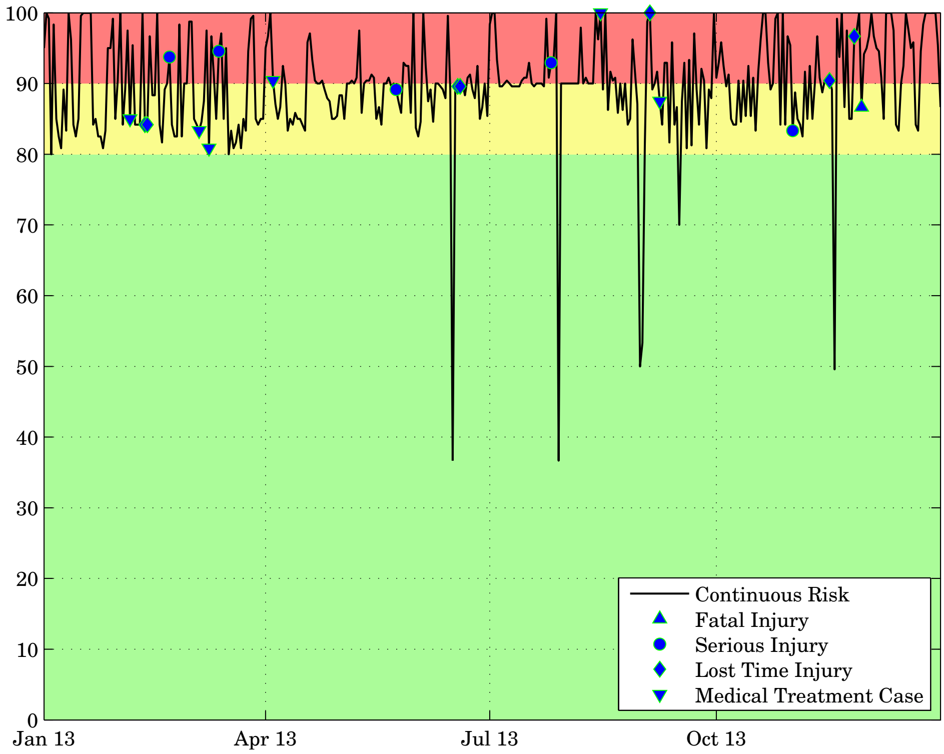


Figure 4.43: Engineering 2011 network predicting 2013 risk

Similarly, for the other sections, the 2012 network which was identified as the best network amongst the other sections networks was run with data for every year from 2009 to 2013. Yet again, this network worked well for 2012 with no outlying accidents and it predicted 2013 fairly well with only three outlying accidents. However, going back in time the continuous risk profiles get progressively worse. Predicting the 2011 continuous risk profile yields three outlying accidents, for the 2010 continuous risk profile there are six outlying accidents and for the 2009 continuous risk profile there are 16 outlying accidents. Figures 4.44 to 4.48 presents the plots of the continuous risk profiles along with the actual accidents from 2009 to 2013 respectively.

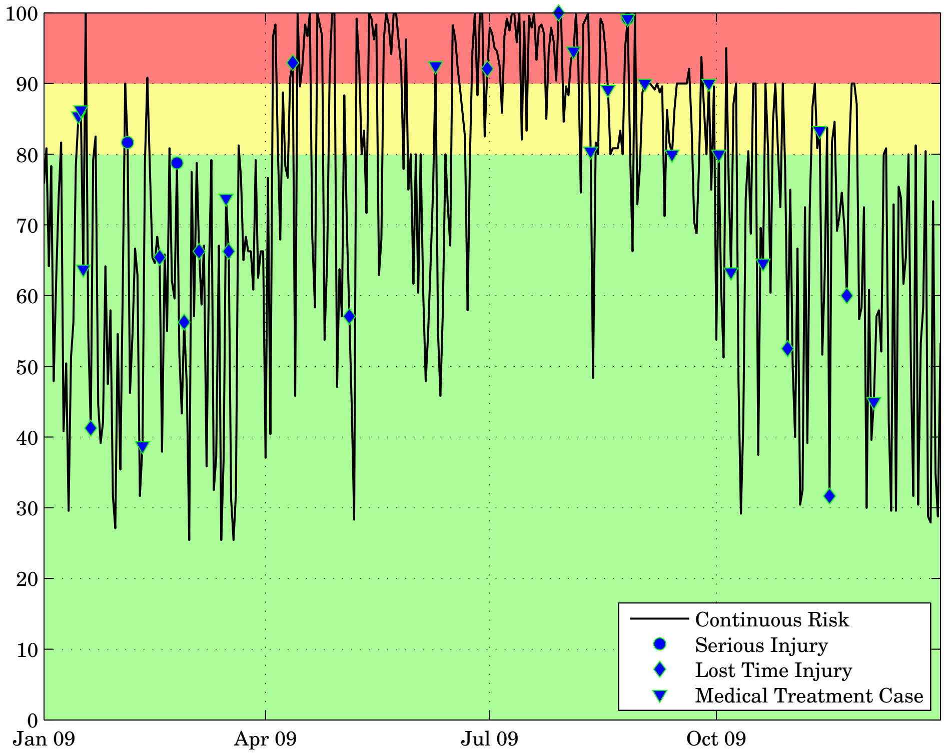


Figure 4.44: Other 2012 network predicting 2009 risk

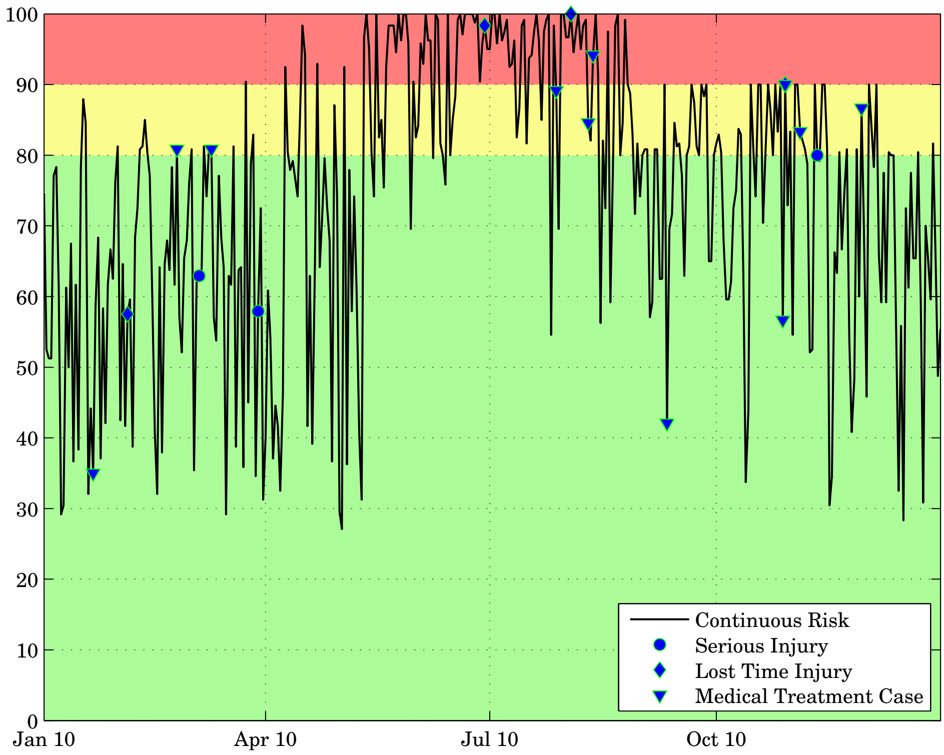


Figure 4.45: Other 2012 network predicting 2010 risk

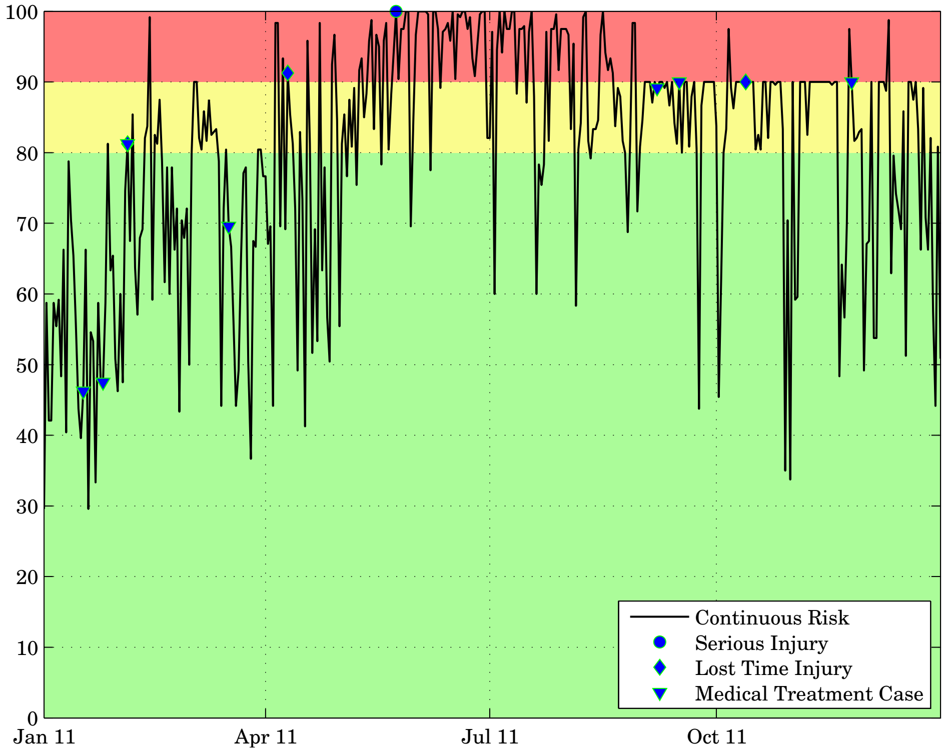


Figure 4.46: Other 2012 network predicting 2011 risk

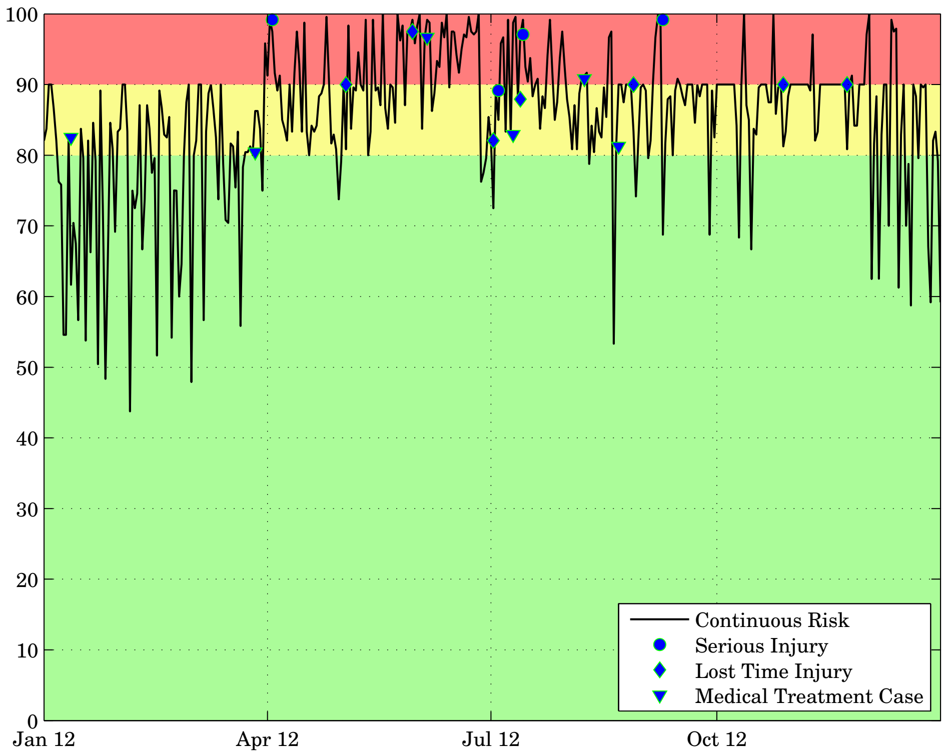


Figure 4.47: Other 2012 network predicting 2012 risk

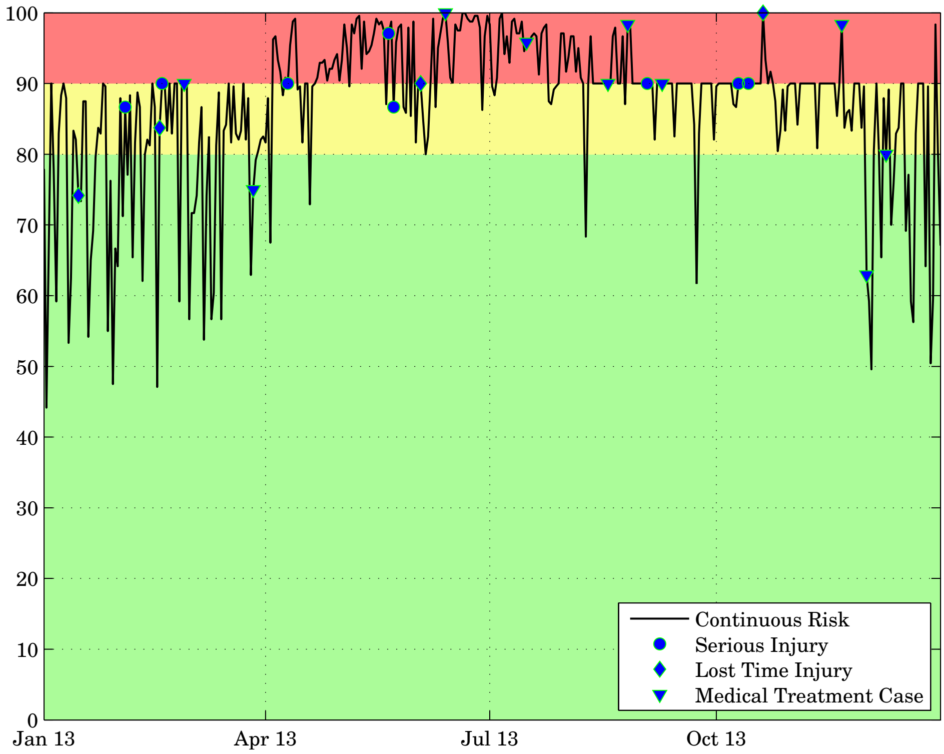


Figure 4.48: Other 2012 network predicting 2013 risk

From Figures 4.39 to 4.48 it can be seen that the networks are suited best for the year they are trained and the following year, and not for any other year. Table 4.21 and 4.22 present the statistics from these plots. Table 4.21 shows that the 2011 engineering network is best suited for 2011 and 2012, with the lowest percentage of outliers, and highest percentage accidents occurring while the continuous risk profile is positive while the rest had a large range. Similarly, Table 4.22 shows that the 2012 other network is best suited for 2012 and 2013, with the lowest percentage of outlying accidents.

Table 4.21: Summary of statistics from engineering 2011 network run over all five years

Year	**2009**	**2010**	**2011**	**2012**	**2013**
Number of accidents	39	20	20	19	19
Minimum risk	10.00%	10.00%	10.00%	10.00%	37.00%
Maximum risk	99.00%	98.00%	100.0%	100.0%	100.0%
% outliers	48.72%	40.00%	5.00%	5.26%	0.00%
% between 80% and 90%	41.03%	50.00%	45.00%	63.16%	57.89%
% between 90% and 100%	10.26%	10.00%	50.00%	31.58%	42.11%
% with positive gradient	51.28%	40.00%	80.00%	68.42%	52.63%

Table 4.22: Summary of statistics from other 2012 network run over all five years

Year	**2009**	**2010**	**2011**	**2012**	**2013**
Number of accidents	33	18	11	17	23
Minimum risk	25.00%	28.00%	30.00%	44.00%	44.00%
Maximum risk	100.0%	100.0%	100.0%	100.0%	100.0%
% outliers	48.48%	33.33%	27.27%	0.00%	13.04%
% between 80% and 90%	30.30%	50.00%	54.55%	41.18%	17.39%
% between 90% and 100%	21.21%	16.67%	18.18%	58.82%	69.57%
% with positive gradient	54.55%	61.11%	63.64%	64.71%	65.22%

From the discussion so far, it can be confirmed why a network is needed for each year that can be used to predict the following year and not just one generic network which can be used indefinitely. Furthermore, from the results it is identified that it is not possible to draw any significant conclusions about the underground section of the mine due to the fact that the underground section is constantly at a high risk of having an accident. Next, the use of the model is discussed.

4.7 Use of the Model

Now that the model has been trained and validated, the method of how the model is intended to be used can be discussed. Firstly, the inputs into the future obviously will not be known, thus the entire years continuous risk profile cannot be pre-determined as it was in the training and validation of the networks above. However, educated estimates of the next weeks or months, temperatures, humidity, rainfall and production rates can be identified and run through the model in order to output the next weeks or months risk profile. The further into the future the inputs are estimated, the larger the chance of error. For example, assuming the date is the 1st March 2012, the next weeks production is estimated to be at 75% of its maximum and the weather forecast predicts the following weather conditions for the week as seen in Table 4.23.

These conditions are manipulated according to the normalised continuous approximations identified in the third chapter and then run through the engineering, other, and underground networks for 2011, however, the networks can continuously be updated on a monthly basis, always using the previous twelve months of accident data for training. For the purpose of this example, the 2011 networks will be used. After the weeks estimated data is normalised, it is run through the three networks, the output is plotted and the actual accidents are included for reference. Firstly Figure 4.49 presents the weeks continuous risk profile for the engineering section, it shows the risk on the first of March is

Table 4.23: Estimated weather conditions

	Max Temp	**Min Temp**	**Humidity**	**Rain**
1st March 2012	31	19	81	yes
2nd March 2012	32	19	65	no
3rd March 2012	33	16	59	no
4th March 2012	37	14	47	no
5th March 2012	37	19	48	no
6th March 2012	30	20	63	no
7th March 2012	32	19	56	no

roughly at 98% and an accident did occur on the first of March, then the risk progressively declines until the fourth of March, then it increases again until the sixth of March and then decreases slightly. From the plot it can be seen that from the third to the sixth of March the risk is below 80% and thus not an issue, furthermore, from the sixth to the seventh of March the continuous risk gradient is negative as well as from the first of March to the fourth of march and thus is not as much of an issue. Hence for the week predicted, the first of March is of concern, as well as from the fifth to the sixth of March, which is where the risk is above 80% and the continuous risk profile has a positive gradient.

Next, the same is done with the other network. As can be seen in Figure 4.50, the risk is mainly below 80%, however, there are two peaks just above 80% that the other sections need to be cautious of. In reality, no accidents occurred in this week for the other section.

Lastly, the same was done with the underground section. As can be seen in Figure 4.51, the risk is constantly above 80%, which identifies that caution needs to be taken the entire week in the underground section. In reality, one accident occurred in this week on the second of March.

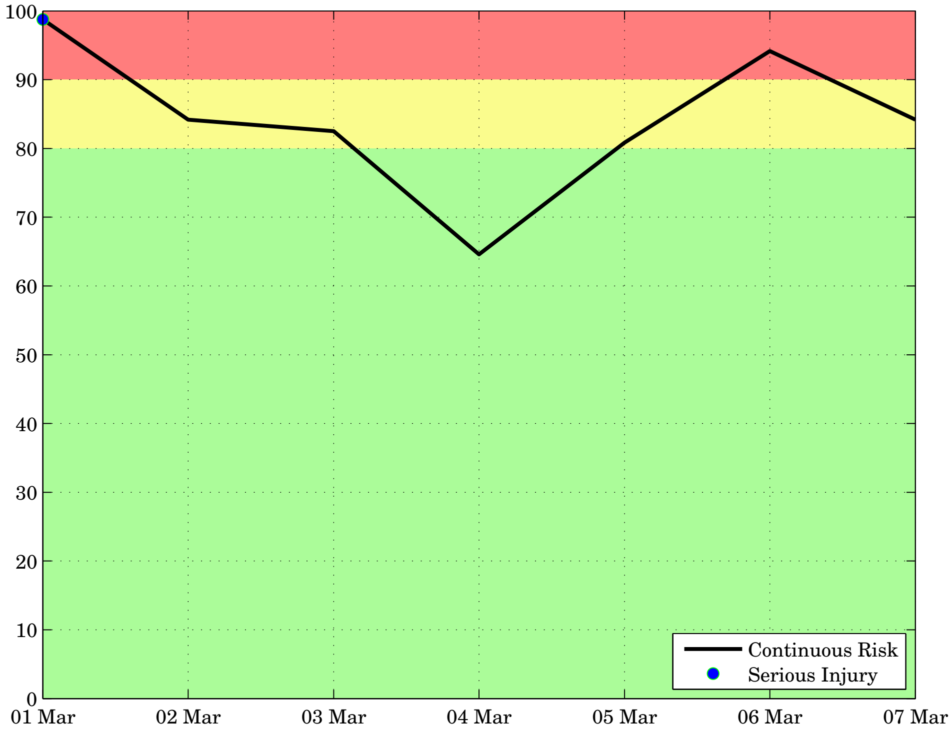


Figure 4.49: Engineering 2011 network predicting weeks estimated risk

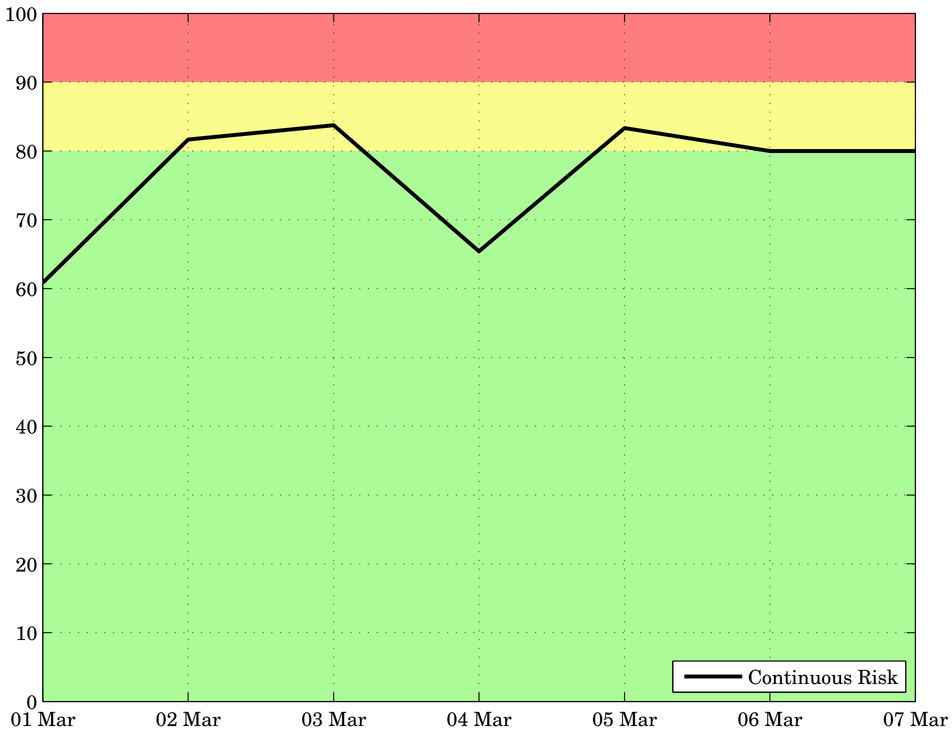


Figure 4.50: Other 2011 network predicting weeks estimated risk

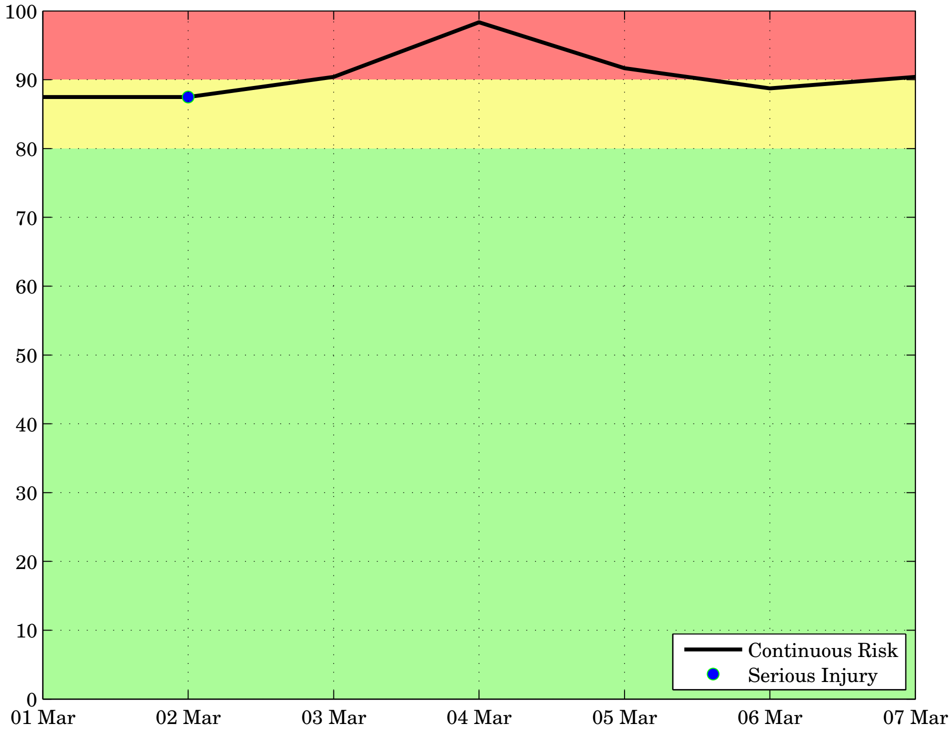


Figure 4.51: Underground 2011 network predicting weeks estimated risk

4.8 Chapter 4 Concluding Remarks

In conclusion from this chapter, it has been proven that the individual networks per year are more applicable than one general network which can be used indefinitely. Furthermore, from splitting the data into three sections, the underground section is identified to be at constant risk of an accident and thus the underground networks are not useful for identifying periods of high risk and low risk, however, the networks for the engineering section and other section appear to work well at highlighting periods of higher risk and lower risk with good correlation to the accidents that actually occurred.

Chapter 5

Conclusion

5.1 Introduction

This chapter serves the purpose of bringing closure to the research and to summarise the entirety of this thesis. This is achieved through an overview of the thesis, followed by the limitations encountered during the research, then some recommendations for future research in this field are discussed and lastly this study is concluded. The intention of this chapter is to deliver a complete overview of the study conducted and understand the limitations that prevented certain results, as well as to identify the possibilities for future research by identifying areas for improvement.

5.2 Overview

In chapter one, the research idea of estimating the continuous risk of accidents occurring in the South African mining industry is introduced. This is then backed up with a background of information regarding mine safety and the risks attached to mining. Furthermore, the proposed research is defined in the form of a problem statement to keep the focus of the research, delimitations to give the research bounds and research objectives to follow in order to keep on track and reach the final result of accepting or rejecting the null hypothesis.

Chapter two takes the form of a literature study, which starts by exploring safety and risk in general, then factors that influence accidents are explored and lastly five modelling techniques are studied and compared. Chapter three follows with presenting the proposed model as a solution to the problem statement. This is followed by an in depth look at the mathematics behind the Artificial Neural Networks (ANN), after which the data obtained to use for this model is analysed and sorted for use in the model.

Lastly, chapter four covers the method as well as the practical aspects of training the model and validating the model, followed by the results and discussion of the outputs. Furthermore, a sensitivity analysis of the network inputs is performed, and a section is included on how the model is intended to be used. Next, the limitations of the research are discussed.

5.3 Limitations

A vital portion of any research is the limitations that are identified during the study. These limitations need to be understood in order to find a way to perform the research around them. The development, training and validation of the model to estimate the continuous risk of accidents occurring came across several limitations which are listed below.

- With occupational accidents, it is statutory to record multiple factors regarding the accident, thus with respect to the accident data, it is abundant and very detailed. This is very useful for training the model in great detail which Artificial Neural Networks (ANN) can handle. However, a large portion of these factors are either not measured or unable to be measured on a continuous time basis. These factors cannot be used in the model due to the fact that the continuous risk profile prediction requires them on a continuous scale. Furthermore, the more factors that are included, the more specific the model becomes, and eventually a model will be required per person, instead of per mining section.

- With the improvements of safety initiatives over the years as well as the complex interactions of various factors that influence accidents changing, a single network is not sufficient to be used to estimate the continuous risk profile indefinitely. Thus in this research, it was chosen to create a network for each year, which was only used to predict its own year and the next year, however, a rolling year would be another possible option, were the network is updated every month always using the previous twelve months accident data and always predicting one month in advance.

- Due to the high risk nature of the work performed by the miners in the underground section of the mine, the model output was a continuous risk profile above 80%, indicating a permanent risk. Although this is correct, it provides no useful information to the underground section with respect to when they are working in a safe zone or not.

- Despite all the factors measured regarding an accident, the variability from human behaviour is unmeasured and has an unpredictable nature. Thus even the best generalised model has the potential to miss accidents as well as predict high risk periods when no accidents actually occur.

- ANN make use of random starting points with the training examples as well as for the splitting of the examples into training, validation and testing. Thus every time the network is retrained, a network independent of the previous network is produced. Therefore, it is possible to settle on a sub-optimum network.

These limitations were overcome and worked around during the process of this research and despite these limitations valid results were obtained. The next section presents recommendations if further research were to be completed in this field of study.

5.4 Recommendations for Future Research

Despite the research objectives being met, there are still areas for improvement. Ideas of improvement areas were noted during the course of this study and this section discusses suggestions that can contribute in improving and adding to this research by means of further research. There are three primary areas where further research can be beneficial.

- As was noted in the limitations, very few influential factors were used in the model due to the availability of data of many of the accidents. A recommendation is made to research more factors that influence accidents, as well as to identify and promote methods of measuring many of these factors on a continuous time basis. This may prove tremendously valuable in creating a more accurate model to estimate the continuous risk of accidents occurring.

- A more detailed literature study can be performed on the probabilities linking the influencing factors to the inputs to the networks. By making use of global statistics and using accident information from multiple industries could possibly prove more accurate than creating the probabilities from the histograms of the actual accidents, furthermore, it could make the model more robust and aid generalisation.

- A limitation was noted that settling on a suitable network is not always possible, and thus a research possibility would be to determine a method that ensures an optimal network is always selected when training the ANN.

All of the recommendations for further research stated above are propositions to advance and progress the research conducted.

5.5 Conclusion

Grimaldi and Simonds (1989) state that not all injuries can be prevented, since they are unpredictable in nature and that accidents do occur at times for reasons that are unpredictable. However, occupational injuries can be brought down to irreducible minimums. The challenge is to identify were the minimum is that no more can be done. This study attempted to assist in highlighting high risk time periods, were caution can be taken in order to reduce the accidents occurring.

As was identified in the previous chapter, the model produced worked well at estimating the continuous risk of accidents occurring across all sections of the mine, however, the results for the engineering section and other section were more useful and the results from the underground section were not as useful due to the risk constantly being above 80%. With this in mind, the null hypothesis can be rejected and it can be said that this study was successful at creating a model which can be used to estimate the continuous risk of accidents occurring in the South African mining industry. Furthermore, if the recommendations for future research are performed and added to this research, the potential of the model to estimate the continuous risk of accidents occurring will increase with the models accuracy increasing as well.

It can be confirmed that at the completion of this study all the research objectives listed in the first chapter have been achieved.

1. Relevant literature was studied and a comprehensive understanding of occupational safety was attained.

2. Relevant literature was studied and various existing forecasting techniques were explored and compared.

3. Relevant literature was studied and contributing factors that influence accidents were identified.

4. The contributing factors that influence accidents were quantified through a data analysis of the accident data received.

5. The sensitivity of the contributing factors that influence accidents was achieved after the networks were trained and validated.

6. A model for estimating the continuous risk of accidents occurring was established.

In closing, this study was successful in estimating the continuous risk of accidents occurring based on data from the South African platinum mining industry, however, due to the versatility of retraining the ANN, the model can easily be adapted and tested in different heavy industrial and labour intensive industries.

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Appendices

Appendix A

Derivation of Back-Propagation Rule

This presents the derivation of the back-propagation weight tuning rule. When updating each weight for each training example d,

$$w_{ij,new} = w_{ij,current} + \Delta wij$$

where:

$$\Delta w_{ij} = -\eta \frac{\partial E_d}{\partial w_{ij}} \tag{A.1.1}$$

where:

$$E_d(\vec{\mathbf{w}}) \equiv \frac{1}{2} \sum_{k \in \text{Outputs}} (t_k - o_k)^2$$

where:

> *Outputs* is the set of output nodes in the network.
>
> t_k is the target value of node k for training example d.
>
> o_k is the output value of node k for training example d.

The following notation is used below for the rest of the derivation,

x_{ij}	$\rightarrow$	the j^{th} input to node i.
w_{ij}	$\rightarrow$	the weight associated with the j^{th} input to node i.
net_i	$\rightarrow$	$\sum_i w_{ij} x_{ij}$ (the weighted sum of all inputs for node i).
o_i	$\rightarrow$	the output computed by node i.
t_i	$\rightarrow$	the target output of node i.
σ	$\rightarrow$	the sigmoid function.
Outputs	$\rightarrow$	the set of nodes in the final layer of the network.

Downstream(i) → the set of nodes whose immediate inputs include the output of node i.

Firstly,

$$\frac{\partial E_d}{\partial w_{ij}} = \frac{\partial E_d}{\partial \text{net}_i}\frac{\partial \text{net}_i}{\partial w_{ij}} \tag{A.1.2}$$

$$= \frac{\partial E_d}{\partial \text{net}_i} x_{ij} \tag{A.1.3}$$

because the weight w_{ij} can only influence the rest of the network through net_i. Now, a convenient expression for $\frac{\partial E_d}{\partial \text{net}_i}$ is required. In order to do this, two cases need to be considered, firstly, when node i is an output node and secondly when node i is an internal node.

Case 1 – Training Rule for Output Node Weights

Similar to w_{ij} only influencing the rest of the network through net_i, net_i can only influence the network through o_i. Therefore,

$$\frac{\partial E_d}{\partial \text{net}_i} = \frac{\partial E_d}{\partial o_i}\frac{\partial o_i}{\partial \text{net}_i} \tag{A.1.4}$$

Focussing just on the first term in Equation A.1.4,

$$\frac{\partial E_d}{\partial o_i} = \frac{\partial}{\partial o_i}\frac{1}{2}\sum_{k \in \text{Outputs}} (t_k - o_k)^2$$

Since the derivatives of $\frac{\partial}{\partial o_i}(t_k - o_k)^2$ will be zero for all outputs nodes k except when $k = i$. Thus the summation can be dropped and $k = i$. Therefore,

$$\frac{\partial E_d}{\partial o_i} = \frac{\partial}{\partial o_i}\frac{1}{2}(t_i - o_i)^2 \tag{A.1.5}$$

$$= \frac{1}{2}2(t_i - o_i)\frac{\partial (t_i - o_i)}{\partial o_i} \tag{A.1.6}$$

$$= -(t_i - o_i) \tag{A.1.7}$$

Next, focussing on the second term in Equation A.1.4, since $o_i = \sigma(\text{net}_i)$, the derivative $\frac{\partial o_i}{\partial \text{net}_i}$ is just the derivative of the sigmoid function. Therefore,

$$\begin{aligned}
\frac{\partial o_i}{\partial \text{net}_i} &= \frac{\partial \sigma(\text{net}_i)}{\partial \text{net}_i} && \text{(A.1.8)}\\
&= \frac{\partial}{\partial \text{net}_i}\left(\frac{1}{1+e^{-\text{net}_i}}\right) && \text{(A.1.9)}\\
&= \frac{e^{-\text{net}_i}}{(1+e^{-\text{net}_i})^2} && \text{(A.1.10)}\\
&= \frac{1+e^{-\text{net}_i}-1}{(1+e^{-\text{net}_i})^2} && \text{(A.1.11)}\\
&= \frac{1}{1+e^{-\text{net}_i}} - \frac{1}{(1+e^{-\text{net}_i})^2} && \text{(A.1.12)}\\
&= \sigma(\text{net}_i) - \sigma(\text{net}_i)^2 && \text{(A.1.13)}\\
&= \sigma(\text{net}_i)(1-\sigma(\text{net}_i)) && \text{(A.1.14)}\\
&= o_i(1-o_i) && \text{(A.1.15)}
\end{aligned}$$

Substituting A.1.7 and A.1.15 into A.1.4,

$$\frac{\partial E_d}{\partial \text{net}_i} = -(t_i - o_i)o_i(1-o_i) \quad \text{(A.1.16)}$$

Combing A.1.16 with A.1.3 and A.1.1,

$$\Delta wij = -\eta \frac{\partial E_d}{\partial w_{ij}} = \eta(t_i - o_i)o_i(1-o_i)x_{ij} \quad \text{(A.1.17)}$$

From this it can be seen that $\delta_k = -\frac{\partial E_d}{\partial \text{net}_k}$.

Case 2 – Training Rule for Hidden Node Weights

As stated before Downstream(i) refers to the set of all nodes immediately downstream of node i. Noting that net_i can only influence the network outputs through the nodes downstream of i. Therefore,

$$\begin{aligned}
\frac{\partial E_d}{\partial \text{net}_i} &= \sum_{k \in \text{Downstream}(i)} \frac{\partial E_d}{\partial \text{net}_k}\frac{\partial \text{net}_k}{\partial \text{net}_i}\\
&= \sum_{k \in \text{Downstream}(i)} -\delta_k \frac{\partial \text{net}_k}{\partial \text{net}_i}\\
&= \sum_{k \in \text{Downstream}(i)} -\delta_k \frac{\partial \text{net}_k}{\partial o_i}\frac{\partial o_i}{\partial \text{net}_i}\\
&= \sum_{k \in \text{Downstream}(i)} -\delta_k w_{ki} \frac{\partial o_i}{\partial \text{net}_i}\\
&= \sum_{k \in \text{Downstream}(i)} -\delta_k w_{ki} o_i(1-o_i)
\end{aligned}$$

Therefore,

$$\delta_i = -\frac{\partial E_d}{\partial \mathrm{net}_i} = o_i(1 - o_i) \sum_{k \in \mathrm{Downstream}(i)} \delta_k w_{ki}$$

and

$$\Delta w_{ij} = \eta \delta_i x_{ij}$$

Appendix B

Confusion Matrix Calculations

A confusion matrix is a specific table layout that allows visualisation of performance. Each column represents the instances in a true class, and each row represents the instance in a predicted class. Figure B.1 shows the layout of the typical confusion matrix. The two classes that can be classified are ‘X’ and ‘Y’.

		True X	True Y	
Prediction	X	A	B	PPV
				1-PPV
	Y	C	D	NPV
				1-NPV
		TPR	TNR	OA
		1-TPR	1-TNR	1-OA

Figure B.1: Generic confusion matrix

In the confusion matrix, the positions are labelled as follows:

A is the true positive

B is the false positive

C is the false negative

D is the true negative

From this, it can be seen that A and D indicate correct classification and B and C indicate misclassification. All values in the confusion matrix can be in number format or percentage format, as long as it is consistent. Using the definitions above, seven calculations can be performed on the confusion matrix.

Firstly, the True Positive Rate (TPR), which is also known as the 'sensitivity', is calculated as follows,

$$\mathrm{TPR} = \frac{\mathrm{A}}{\mathrm{A} + \mathrm{C}} \tag{B.1.1}$$

Secondly, the True Negative Rate (TNR), which is also known as the 'specificity', is calculated as follows,

$$\mathrm{TNR} = \frac{\mathrm{D}}{\mathrm{B} + \mathrm{D}} \tag{B.1.2}$$

Next, the Positive Predictive Value (PPV) is calculated as follows,

$$\mathrm{PPV} = \frac{\mathrm{A}}{\mathrm{A} + \mathrm{B}} \tag{B.1.3}$$

Next, the Negative Predictive Value (NPV) is calculated as follows,

$$\mathrm{NPV} = \frac{\mathrm{D}}{\mathrm{C} + \mathrm{D}} \tag{B.1.4}$$

Then, the average accuracy is calculated as follows,

$$\text{Avg. Accuracy} = \frac{\mathrm{TPR} + \mathrm{TNR}}{2} \tag{B.1.5}$$

Then, the average reliability is calculated as follows,

$$\text{Avg. Reliability} = \frac{\mathrm{PPV} + \mathrm{NPV}}{2} \tag{B.1.6}$$

Lastly, the overall accuracy is calculated as follows,

$$\mathrm{OA} = \frac{\mathrm{A} + \mathrm{D}}{\mathrm{A} + \mathrm{B} + \mathrm{C} + \mathrm{D}} \tag{B.1.7}$$

The confusion matrix is not bound to classification of only two classes, it can be expanded to multiple class classification.